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(Un)expected Housing Price Changes: Identifying the Drivers of Small Business Finance

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Although the most recent housing crisis in the United States triggered the most severe recession since the Great Depression, little is known about the effect of housing prices on small business finance. In this paper, we use the Kauffman Firm Survey to document the significant effect of housing price changes on several measures of borrowing by small business owners. Furthermore, we use macroeconomic forecasting techniques to decompose housing price changes into expected and unexpected components. We find that the largest responses of small business borrowing variables are to the unexpected—surprise—component and occur with a lag of about four years. In contrast, the response to the anticipated changes never significantly exceeds that of observed housing price changes and declines over time.

Keywords: Small business finance; house price changes; forecasting

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I. Introduction

Small businesses are considered essential for economic growth and vitality. Previous studies (e.g. Headd, 2010) suggest they generate employment during recessions, when the marginal value of a dollar of a household's income is relatively high. The success of small business enterprises depends critically on the owner's access to financial capital, both in explaining start-up behavior and continued success of the small business. Recent evidence suggests that firms rely heavily on debt financing and that those using business debt financing, are more likely to survive and grow (Robb and Robinson, 2014; Cole and Sokolyk, 2013). Further, Robb and Robinson find that housing markets play an important role in firm financing as access to debt is greater when housing is a more plausible source of collateral. Analyzing the role of financial capital access in business creation, however, is complicated. In particular, selection into self-employment or small business ownership is clearly non-random and is very likely correlated with financial capital prior to start-up (Blanchflower and Oswald, 1998; Manser and Picot, 1999; Hurst and Lusardi, 2004). Moreover, small businesses often rely on complex and "informationally opaque" private equity contracts, which exacerbates empirical efforts to explain underlying financing behaviors (Berger and Udell, 1998).

In this study, we capitalize on the unexpected shock to credit markets caused by the recent housing market crash in the U.S, which though pervasive, varied in severity across states. Given that a non-trivial portion of small businesses rely on mortgage loans to finance their business activities (Mach and Wolken, 2006; Muske et al 2009; SBA Advocacy, 2012), shocks to the housing market prices can affect small business financing substantially. Our identification strategy, therefore, allows us to isolate the effect of wealth on access to capital for small businesses and hinges on the assumption that housing price changes during the recent downturn were exogenous. We use firm-level data from the Kauffman Firm Survey merged to housing market data from the Federal Housing Finance

Agency (FHFA) from 2000 to 2010 in order to examine the effect of changes in wealth caused by the housing downturn on business credit, small-business employment, and firm growth.

Our decomposition of actual housing price changes into expected (forecasts) and unexpected (forecast errors) components has important differences with measures of housing price shocks that have been used in the related literature on entrepreneurship to date. Much of the entrepreneurship literature that has used housing prices as a measure of wealth and its impact on entrepreneurial employment outcomes has either used historical prices, as in the recent work by Adelino et al (2014), or residuals from regressing one-year cross-sectional or multiyear panel regressions of housing price growth on local demographic characteristics and macroeconomic conditions, as in Fairlie and Krashinsky (2012). The former approach does not measure housing price surprises and the latter measures only the cross-sectional departures of housing price growth in particular locations from the expected level given by macroeconomic and demographic conditions. Our forecasting approach, in contrast, allows for surprises in the time-series dimension that may reflect unexpected housing price changes associated with the turning points in the business and housing cycles. Furthermore, we incorporate the forward-looking information that may be available to the public in real time and affect that planning of financial activities by incorporating the forecasts from the Survey of Professional Forecasters. This method is particularly relevant for large housing market disturbances, such as the one that triggered the most recent recession, because they are not fully anticipated ahead of time.

The rest of the paper is organized as follows. In Section II, we begin with an overview of related literature on small business finance and the effects of housing price changes on it. We then describe our empirical approach. Our data can be divided into two main categories: macroeconomic data from multiple publicly available sources and firm-level microeconomic data from the Kauffmann Firm Survey. In Section III, we conduct a macroeconometric exercise decomposing the actual or observed housing price changes into the expected component, given by forecasts, and the unexpected component given by the forecast error. In Section IV, we set up the microeconometric exercise that is central to this paper. In one set of specifications, we regress measures of small business borrowing on actual housing price changes, controlling for the state-level macroeconomic conditions, given by the unemployment rate, as well as a large number of firm and owner characteristics. In the other set of specifications, we replace the actual housing price changes with forecasts and forecast errors to isolate the expected and unexpected components of housing price changes. In Section V, we discuss the microeconometric results and show that while the response of small business borrowing measures to actual price changes remains relatively constant over long periods of time, their sensitivity to the expected component declines and to the unexpected one—increases. This finding suggests that the full effect of large housing price changes may take a protracted period of time in manifesting its impact on small business finance. Finally, Sections VI offers concluding remarks.

II. Previous literature

A. Small Business Ownership & Financing

A large body of literature that suggests wealthier individuals are more likely to start a business, suggesting that lack of access to financial capital may prevent entrepreneurial ventures (Evans and Jovanovic, 1989; Evans and Leighton, 1989; Meyer, 1990; Holtz-Eakin, Joulfaian, and Rosen, 1994; Lindh and Ohlsson, 1996, 1998; Blanchflower and Oswald, 1998; Fairlie, 1999; Dunn and Holtz-Eakin, 2000; Johansson, 2000; Holtz-Eakin and Rosen, 2005; Giannetti and Simonov, 2004; and Bates and Lofstrom, 2008; Zissimopoulos and Karoly, 2007, 2009). Recent work, however, suggests a more nuanced interpretation of these findings. Hurst and Lusardi (2004) find that the positive relationship between wealth and business outcomes seems to be driven almost entirely by individuals in the far right tail of the asset distribution. A follow-up study suggests that the relationship between financial capital and business creation and success may vary considerably by one's previous employment status (Fairlie and Krashinsky, 2012). In their study, Fairlie and Krashinsky (2012) suggest that individuals who become self-employed because they lost a wage-and-salary job behave differently than individuals who otherwise select self-employment. They find that more wealth leads to higher rates of entry into self-employment even for those with low levels of wealth.

For this analysis, we draw on previous theoretical models of the decision to become self-employed (Evans and Jovanovic, 1989; and Fairlie and Krashinsky, 2012). In essence, individuals choose self-employment when their expected net income from self-employment exceeds their expected wage-and-salary income. The wage-and-salary income depends on their experience, education, and the market wage. The expected entrepreneurial earnings depend on entrepreneurial ability and capital investment. Individuals with lower assets or access to financial capital will both be less likely to choose self-employment and have lower capital investments if they do choose self-employment. These models imply that initial capital investments are drawn largely from personal savings and loans from friends and family. Therefore, because personal savings and assets play into both the decision to select into self-employment and capital expenditure decisions when self-employed, any empirical estimation of the relationship between assets (or correlated measures, such as access to financial capital) and entrepreneurial success or outcomes will be biased.

Small business sources of financing include a wide range of contracts, including private equity sources. Most small businesses, however, rely on some debt financing. For example, data from the most recent National Survey of Small Business suggests that over 60 percent of small businesses use any type of credit line, loan or capital lease for business financing (Mach and Wolken, 2006). Moreover, small business' capital structure is about 50 percent debt, even among younger firms (Berger and Udell, 2003). Although the effect of an exogenous shock to the housing market likely affects all sources of small business financing, we focus on easier to measure debt financing sources in this study.

B. The Housing Market Decline of 2008

The most recent housing crisis devastated the US economy and triggered the so-called Great Recession—the most severe downturn since the Great Depression of the 1930s. Home prices dropped by about 30 percent from 2006 to the trough in 2009.[1] This mean change, however, masks the considerable variation across the U.S. where some states experienced at least a 40 percent growth in housing prices from 2006 to 2010, while others experienced a decrease of more than 40 percent over the same time period.[2] This large disturbance, however, offer a potential source of exogenous change in the value of individuals' assets and wealth such that we can empirically isolate effects of wealth on small business financing and entrepreneurial success. Small business owners who owned a home and experienced declines in their housing wealth presumably had less (or even negative) home equity to use as collateral for business-related loans. The sharp decline in housing prices might also have led business owners to shift their financial efforts from real estate, including primary and secondary residences, toward their businesses. How the decline in housing prices might have affected the 18 percent of small business owners who did not own a home is less clear, as they may have viewed the decline as an impetus to purchase (Bricker et al., 2012). Previous studies have estimated that between 13 and 20 percent of small businesses held mortgage debt or used at least one home mortgage to finance business expenses (Mach and Wolken, 2006; Dennis, Jr., 2010).

Broadly, the costs of the crisis and the recession were largely borne by the financial system, increasing credit risk and decreasing lending for not only mortgages but for a wide range of lending instruments (Holt, 2009). Recent research suggests that decreases in lending were particularly acute for small businesses (Cole, 2012), that small exporters lost market share (Peek, 2013), and that healthier banks were less likely to lend to smaller

[1] This is based on analysis of the Case-Shiller 20-City Home Price Index. Data available from http://research.stlouisfed.org/fred2/series/SPCS20RSA.

[2] Statement based on Housing Price Index data from the Federal Housing Finance Agency. A summary map can be found at: http://www.huffingtonpost.com/2011/04/27/housing-market-prices-chart-recession_n_854388.html.

firms (Peek, 2011). For example, the number of business owners holding a business loan or line of credit declined 20 percent in 2009 and about 40 percent of business owners reported that their credit needs were met somewhat or not at all from 2009-2011 (Dennis, Jr., 2010, 2011; NFIB, 2012). However, unmet credit needs were only identified by 2 percent of owners as their top concern in 2014 (Dunkelberg and Wade, 2014).

Evidence suggests declines in small business lending not just since the 2008 housing collapse, but since the late 1990s (Shane and Wiersch, 2013). However, whether this is due to demand side factors (small business owners slowing down and asking for less credit) or due to supply side factors (increased lending regulations and collateral requirements) is unclear. While real estate prices have fallen, little is known about the causal link between the most recent housing market crash and small business financing decisions. Previous work suggests that lenders tend to use small business owners personal credit scores instead of their small business credit score for making lending decisions (Berger, Cowan, and Frame, 2010), implying that declines in housing value that negatively affect personal credit scores may influence small business borrowing.

In this study, we aim to provide causal evidence on the effect of an exogenous shock to wealth, in this case through an exogenous change in the housing market, on small business financing. Although we expect exogenous shocks in housing price changes to affect alternative sources of financing (e.g. private equity, etc.), we focus on the following debt financing measures in this study due to data constraints: total small business debt financing, total owner debt financing, whether the owner had more personal debt than business debt, and the number of loan applications.

III. Macroeconometric Stage: Forecasting Housing Price Growth

A. Macroeconomic Data

All macroeconomic data are quarterly and span the 1976q1—2011q4 period. Housing price indices for state *i* at time period *t*, Y_{it}, are from Federal Housing Finance Agency (FHFA). These are weighted, repeat-sales indices that measure average price changes in repeat sales or refinancings on the same properties.[3] The house price indices have been transformed to construct annualized growth rates: $\Delta y_{it} = 400(\ln Y_{it} - \ln Y_{it-1})$. Ex-post macroeconomic data are from the FRED2 database maintained by the St. Louis Federal Reserve. National series include the following (transformation applied to levels):

- Average weekly hours of production and nonsupervisory employees: manufacturing (difference);
- 4-week moving average of initial unemployment claims;
- ISM manufacturing: new orders index (annualized log difference);
- Real M2 money stock (annualized log difference);
- Term spread: difference between the 10-year treasury constant maturity rate and the effective federal funds rate;
- Industrial production index (annualized log difference);
- New private housing units authorized by building permits (annualized log difference);
- Personal consumption expenditures (PCE) implicit price deflator (annualized log difference);
- All-transactions house price index (ATHPI) for the United States (annualized log difference);
- Mortgage rate (difference);
- Real S&P 500 stock market index (annualized log difference).[4]

State-level data from the FRED2 database include the following:

- Unemployment rate (difference);
- House price index (annualized log difference);
- Total personal income (annualized log difference);

[3] Further information about the indices is available at http://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index.aspx.

[4] This series was obtained from Robert Shiller's website.

- Dividends, interest, and rent (annualized log difference);

Survey of Professional Forecasters data are from the Philadelphia Federal Reserve website whereas their matching ex post series are from the St. Louis Fed FRED2 database. The following series are included:

- Real GDP (annualized log difference);
- Housing price index (annualized log difference);
- Unemployment rate (difference);
- Corporate profits (annualized log difference);
- Industrial production index (annualized log difference).

Because the SPF forecast data are made in levels for 1 through 6 quarters ahead, forecast (log) differences are available 2 through 6 quarters ahead. Firm level (KFS) data, with which we need to merge the forecasts and forecast errors, are annual. Since the quality of forecasts generally declines with horizon, we assume that the small business owners build their forecasts as of the third quarter of the year preceding the KFS release and use the average forecast over the subsequent five quarters (one before the KFS year and four during) to average out the forecasts.

Below, we lay out the setup for several approaches for obtaining forecasts of state-level housing price growth rates. We compare them using the root mean square forecast error (RMSFE) obtained over the 1998q3—2011q4 evaluation period, whereby 5-quarter-ahead forecast errors are constructed in every quarter starting in 1998q3. The choice of the starting date for the evaluation period is driven by our aim to (verb missing here) housing price measures lagged up to 5 years relative to the KFS data that start in 2004.

B. Forecasting Approach and Results

In this section, we consider several methods for generating forecasts of housing price changes. These include the standard autoregressive model as the benchmark along with equally standard autoregressive distributed lag (ARDL) models that rely on ex post national and state-level macroeconomic drivers of housing price growth. We supplement these approaches by considering real-time forecasts from the Survey of Professional Forecasters as the exogenous drivers in the ARDL framework. We show that, especially in combination with the standard forecasting methods, their use delivers more efficient state-level housing price change forecasts.

Dependent variable and the AR benchmark model

Following the convention established by Stock and Watson (1999, 2003) and the application to housing price growth forecasting of Rapach and Strauss (2009), we construct $y_{t+h}^{h} = \frac{1}{h}\sum_{j=1}^{h} \Delta y_{t+j}$, so that y_{t+h}^{h} is the approximate price growth from *t* to *t*+*h*, where *h* is the forecast horizon. Given the discussion in the data section, we set h=5 and form forecasts as of the third quarter preceding the year of the KFS release.

The benchmark autoregressive (AR) model is given by estimating the following specification:

$$y_{t+h}^{h} = \alpha + \sum_{j=0}^{q_y-1} \beta_j \Delta y_{t-j} + \epsilon_{t+h}^{h} \qquad (1)$$

and the forecast errors as:

$$e_{t+h}^{h} = y_{t+h}^{h} - \hat{y}_{t+h|t}^{h}, \qquad (2)$$

where the last term represents recursively constructed pseudo-out-of-sample forecasts. The number of lags, q_y, is selected using the Schwarz criterion with the maximum value of 8. The RMSFE is constructed by collecting the forecast errors over the evaluation period and reported for each state in the first column of Table XX, representing a comparison benchmark for models that use exogenous regressors.

ARDL models with ex post data

As is standard in the literature, with Rapach and Strauss (2009) as the most closely related example, forecasters may augment information about the left-hand-side variable by including additional right-hand-side variables and transforming the AR framework given by (1) into its autoregressive distributed lag (ARDL) counterpart by means of adding an exogenous regressor, x_i:

$$y_{i,t+h}^{h} = \alpha_i + \sum_{j=0}^{q_y-1} \beta_{i,j} \Delta y_{t-j} + \sum_{j=0}^{q_x-1} \gamma_{i,j} x_{i,t-j} + \epsilon_{i,t+h}^{h}. \qquad (3)$$

The number of lags for y and x terms is constructed using Schwartz criterion for any combination of q_y and q_x with 8 as the maximum for both. We consider two sets, from which x_i candidates are drawn: the national macroeconomic series and the state-level macroeconomic variables described in the previous section. For each set, we construct average forecast by taking simple averages across the respective $\hat{y}_{i,t+h}^{h}$. The results are reported under the ARDLn (national) and ARDLs (state-level) headings.

ARDL models with SPF forecasts

One contribution of this paper is to evaluate whether the mean forecasts from the Survey of Professional Forecasters conducted in real time may help forecast housing price growth. To incorporate them in our framework, we change the timing assumption on the exogenous variable in (3) as follows:

$$y_{i,t+h}^{h} = \alpha_i + \sum_{j=0}^{q_y-1} \beta_{i,j} \Delta y_{t-j} + \sum_{j=0}^{3} \gamma_{i,j} x_{i,t+h-j} + \epsilon_{i,t+h}^{h}, \qquad (4)$$

where the lag order for y terms comes from the autoregressive specification estimated for the same period and the lag polynomial suggests that in the estimation stage the x values concurrent with y^h and 3 lags are used. Forecasts are then formed on the basis of information available in real time, so that j=[0,1,2,3] lag of x is given by the [5,4,3,2]-quarter-ahead SPF estimate as follows:

$$\hat{y}_{i,t+h}^{h} = \hat{\alpha}_i + \sum_{j=0}^{q_y-1} \hat{\beta}_{i,j} \Delta y_{t-j} + \sum_{j=0}^{3} \hat{\gamma}_{i,j} x_{i,t}^{h-j}, \qquad (5)$$

where the notation on the x term provides a general description of the timing assumptions: it is the real-time forecast of x_i at time t made at most h=*5* quarters ahead. Forecasts obtained for individual macroeconomic series are averaged and appear under the ARDLrt (real-time) heading. Again, the RMSFE is calculated on a recursive quarterly basis over the evaluation period and information as of the third quarter prior to the KFS year for the forecast/forecast-error combinations is employed, for the second stage of our exercise.

Our last model (AvAv) creates an average-of-averages forecast by taking a simple average of all four forecasting models described above: AR, ARDLn, ARDLs, and ARDLrt.

Evaluating forecasts from alternative models

Columns 2—6 of Table 1 document the performance of alternative forecasting models. Although the evaluation period for our exercise is different than the one considered by Rapach and Strauss (2009), the RMSFEs for the AR model reported in column 2 are broadly consistent with the ones that they report for the 20 states in their sample. Adding more explanatory variables on the right-hand-side and averaging across them for any given information set generally leads to forecasting improvement. This improvement is the smallest with state-level variables. Forecasts based on the SPF and national data deliver roughly the same forecasting gains, while the largest improvement obtains in the model that averages across all methods, with all but two states improving on their AR RMSFEs. We conclude that the use of real-time forecasts improves the forecasting efficiency for state-level housing price growth.

IV. Microeconometric Stage: Small Business Borrowing Sensitivity to Housing Price Changes

A. Data and Estimation Framework

Our firm-level data are from the Kauffman Firm Survey. These data are annual and cover 2004—2011, which spans the time period before the most recent recession, the entire recessionary period, and at least part of the recovery. We focus on the following measures of borrowing as dependent variables:

- Categorical measure of total debt of the small business with the following categories:
- Categorical measure of total debt of owner with the following categories:
- Dichotomous measure equal to one if the owner had more personal debt than business debt at the time of the survey and zero, otherwise

- Dichotomous measure of whether the small business applied for any type of loan application in the previous 12 months and zero, otherwise

For every firm *i* in state *j* in year *t*, we designate these financing variables as $f_{ij,t}$ and estimate the following specification:

$$f_{ij,t} = \alpha_i + \beta y_{i,t-r} + \Gamma Z_{ij,t-1} + \delta u_{j,t}. \qquad (6)$$

where, y is the average house price in year $t-r$, where setting $0 \leq r \leq 5$ allows us to trace the dynamic effect of the housing price change on f[5]; u is the unemployment in state *j* in year *t*, which controls both for the business cycle conditions and their heterogeneity across states. In addition to the time-invariant firm-level fixed effects (λ), Z is a set of lagged firm-level controls that include the following:

- Categorical number of owners (1, 2, 3+)
- Presence of a patent or trademark (0/1)
- Presence of personal debt in firm financing structure (0/1)
- Presence of business debt in firm financing structure (0/1)
- Categorical measure of percent of sales to individuals (0, 1-40, 41-90, 91-100)
- Categorical measure of number of employees (0, 1-5, 6+)

We also consider an alternative to (6) that decomposes housing price growth into its expected component given by the forecast from the "average-of-averages" approach, $\hat{y}_{i,t}$, and the forecast error associated with that method, $e_{i,t}$:

$$f_{ij,t} = \alpha_i + \beta_y \hat{y}_{i,t-r} + \beta_e e_{i,t} + \Gamma Z_{ij,t-1} + \delta u_{j,t}. \qquad (7)$$

We estimate (6) and (7) as linear regressions even though most of our outcome measures are not continuous variables. We will test the sensitivity of these results to other specifications in future versions. In the next subsection, we present the results from estimating (6) and (7).

[5] Housing price growth variables were measured in % per year. For the second stage of our exercise, we divide them by 100 to allow for a more parsimonious reporting of the coefficients, which can be interpreted as the effect of a one basis point change in the housing variable.

V. Estimation Results

In Table 2, we present descriptive statistics of our final analytic sample. Approximately 13 percent of the firms in our sample reported applying for a loan in the previous 12 months and 30 percent of owners have more personal debt than business debt. Nearly 50 percent of small businesses have no debt from 2004 to 2011 in our sample, but almost 10 percent have over $100,000 in debt. The majority of the small businesses in our sample have only one owner (63 percent) with five or fewer employees (84 percent). Figures 1 through 4 provide a visual summary of the coefficient estimates and their confidence intervals for the housing variables in (6) and (7). Figures 1 and 2 describe the results for total debt and total debt of owners. The dynamic responses of the two variables are quite similar. Over the first four years, including lag 0, the response of these measures to current and past housing price changes remains relatively constant: 1 basis-point increase in housing price generates about a 1.5% increase in both debt measures. House price growth forecasts produce nearly identical responses within that time span but start getting much smaller in years 3 and thereafter. Forecast errors, on the other hand, have smaller effects in years 0 and 1, are essentially the same as actual housing price changes in years 2 and 3 and become considerably larger after that. In year 4, the peak response of debt to a housing price surprise is about 50% larger (approximately 3.15 vs 2.1) than the peak response to the actual housing price change.

Figure 3 reports a similar pattern for increases in personal debt, although for this variable the effect of the housing price surprise is larger than for the previous two measures. The peak response, which again happens in year 4, is over 60% larger (0.39 vs 0.24) than the peak response to the actual housing price change. Finally, Figure 4 reports that this effect is largely absent for loan applications, as both forecast and forecast error effects track those of the actual price change closely in almost all years.

VI. Conclusion

In this paper, we employ an alternative two-stage empirical strategy to create a more precise measure of unexpected changes in housing wealth by relying on real-time forecasts of key housing and macroeconomic variables. In the macroeconometric part of the exercise, we have shown that the use of real-time forecasts from the Survey of Professional Forecasters that employ a wide variety of data that are available to the forecasters and likely inform the public discourse on the direction of the macroeconomy results in improved forecasts of housing price changes. Using the best performing forecasting strategy, we have shown, in the microeconometric portion of the paper, that for three out of four measures of small business borrowing housing price changes have significant effects for up to 4 years. Initially, it appears that their predictable component drives most of the changes. However, with the passage of time forecast errors or surprising changes in housing price growth begin to matter more and have the largest impact on small business financing decisions.

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Appendix A: Tables

[1] State Name	[2] AR	[3] ARDLn/AR	[4] ARDLs/AR	[5] ARDLrt/AR	[6] AvAv/AR
AK	4.45	0.98	1.02	1.16	1.03
AL	3.88	0.95	0.99	0.96	0.97
AR	2.82	1.05	0.89	0.95	0.96
AZ	8.81	0.99	1.01	1.00	1.00
CA	6.52	0.99	1.01	1.02	1.00
CO	2.33	0.99	0.94	1.03	0.98
CT	3.65	0.95	0.98	0.98	0.98
DC	5.56	0.96	1.01	1.00	0.99
DE	5.44	1.03	1.03	0.90	0.99
FL	9.37	1.00	0.99	0.97	0.99
GA	3.21	0.93	0.89	0.95	0.94
HI	10.13	0.91	0.93	0.96	0.95
IA	1.84	1.22	0.98	0.94	1.02
ID	5.93	1.01	1.02	0.98	1.00
IL	4.28	1.08	1.09	0.96	1.03
IN	1.85	0.98	0.98	0.99	0.98
KS	1.36	0.99	1.00	0.92	0.97
KY	1.83	0.98	1.02	0.97	0.99
LA	2.11	0.93	1.00	1.05	0.98
MA	3.30	1.00	0.98	0.99	0.99
MD	5.01	0.97	0.99	1.00	0.99
ME	3.81	0.98	0.96	1.00	0.98
MI	4.27	0.91	0.96	1.02	0.96
MN	3.25	1.01	0.99	0.93	0.98

Table 1A: AR forecasting RMSFEs (column 2); and the RMSFE ratios for alternative forecasting methods (columns 3—6).

[1] State Name	[2] AR	[3] ARDLn/AR	[4] ARDLs/AR	[5] ARDLrt/AR	[6] AvAv/AR
MO	2.57	0.96	0.99	0.88	0.95
MS	3.77	0.96	0.92	0.94	0.95
MT	4.54	0.99	1.03	0.99	1.00
NC	2.67	0.91	0.98	0.94	0.96
ND	2.65	0.97	0.92	1.10	0.98
NE	1.52	1.02	1.07	0.90	0.99
NH	3.73	1.01	1.00	0.98	0.99
NJ	3.94	0.94	1.01	0.97	0.98
NM	3.68	0.97	0.99	1.05	1.00
NV	9.29	1.00	1.02	0.99	1.00
NY	3.75	0.96	1.00	0.97	0.98
OH	2.24	1.04	1.05	0.98	1.02
OK	1.29	0.97	1.23	1.01	0.94
OR	4.83	1.03	0.98	0.92	0.98
PA	3.03	0.96	1.01	0.95	0.98
RI	4.90	0.99	0.99	0.98	0.99
SC	2.85	0.88	1.00	1.04	0.98
SD	2.95	0.93	1.02	0.82	0.92
TN	2.85	1.05	1.08	0.98	1.02
TX	1.52	0.88	1.17	1.17	0.93
UT	4.81	0.99	0.95	0.99	0.97
VA	4.40	0.99	0.99	0.95	0.98
VT	5.51	0.95	0.83	0.90	0.92
WA	4.57	0.95	0.99	1.02	0.99
WI	3.99	1.11	1.10	0.91	1.02
WV	3.68	0.89	0.87	0.94	0.92
WY	3.11	0.96	0.99	1.09	0.93
Averages		0.98	1.00	0.98	0.98
#<1		36.00	29.00	36.00	42.00

Table 1B: AR forecasting RMSFEs (column 2); and the RMSFE ratios for alternative forecasting methods (columns 3—6).

Table 2. Descriptive Statistics of KFS Sample			
	Mean	Std.Dev.	n
Applied for loan in last 12 months (0/1)	0.13	(.34)	10,339
Owner has more personal debt than business debt (0/1)	0.30	(.46)	16,529
Total Firm Debt (% in each category)			16,529
$0	0.48	(.5)	
$500 or less	0.03	(.16)	
$501 to $1,000	0.02	(.14)	
$1,001 to $3,000	0.05	(.22)	
$3,001 to $5,000	0.04	(.2)	
$5,001 to $10,000	0.06	(.24)	
$10,001 to $25,000	0.10	(.29)	
$25,001 to $100,000	0.14	(.34)	
$100,001 to $1,000,000	0.08	(.27)	
$1,000,001 or more	0.01	(.1)	
Total Owner Debt (% in each category)			16,524
$0	0.57	(.5)	
$500 or less	0.03	(.16)	
$501 to $1,000	0.02	(.14)	
$1,001 to $3,000	0.06	(.24)	
$3,001 to $5,000	0.04	(.2)	
$5,001 to $10,000	0.06	(.25)	
$10,001 to $25,000	0.09	(.28)	
$25,001 to $100,000	0.09	(.29)	
$100,001 to $1,000,000	0.04	(.19)	
$1,000,001 or more	0.00	(.04)	
Total Number of Owners			16,441
1	0.63	(.48)	
2	0.26	(.44)	
3+	0.10	(.3)	
Firm Patent/Trademarks			16,529
0	0.86	(.35)	
1	0.08	(.27)	
1+	0.06	(.24)	
Percent of Sales to Individuals (not to other businesses)			16,529

0%	0.31	(.46)	
1-40%	0.22	(.41)	
41-90%	0.20	(.4)	
90%+	0.27	(.45)	
Employees			16,425
0	0.43	(.49)	
1-5	0.41	(.49)	
6+	0.16	(.37)	

Appendix B: Figures

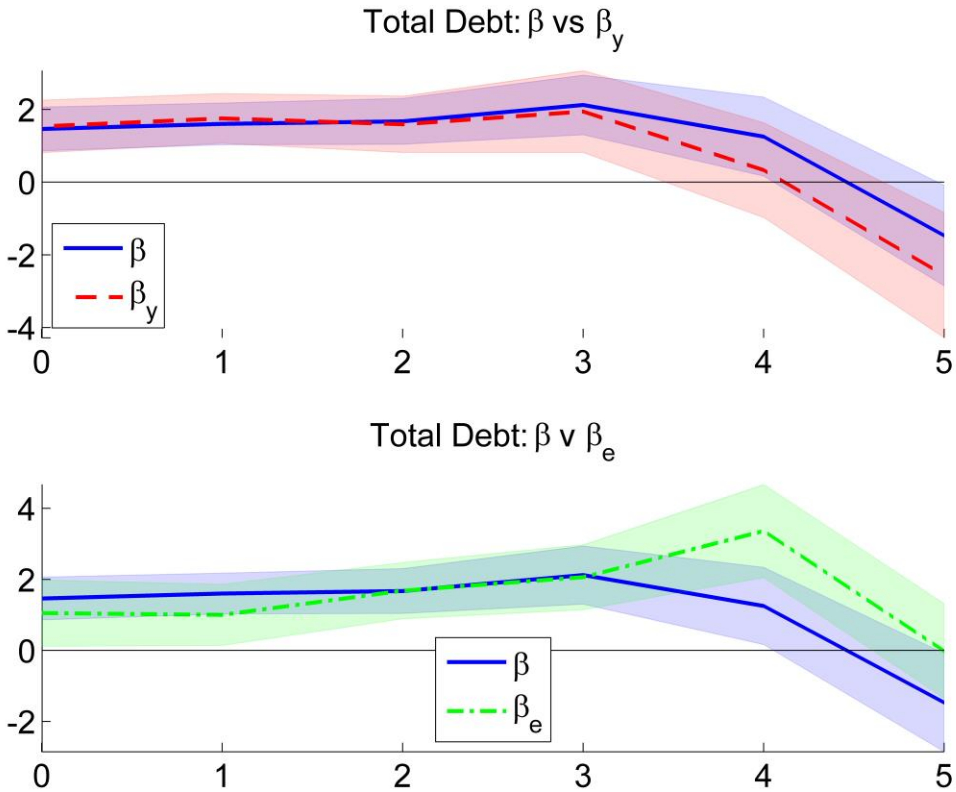

Figure 1: Coefficient estimates across different lags ±2 standard deviations for <u>total debt</u> regressions. Top panel: HPI growth (blue) vs forecast (red); bottom panel: HPI growth (blue) vs forecast error (green).

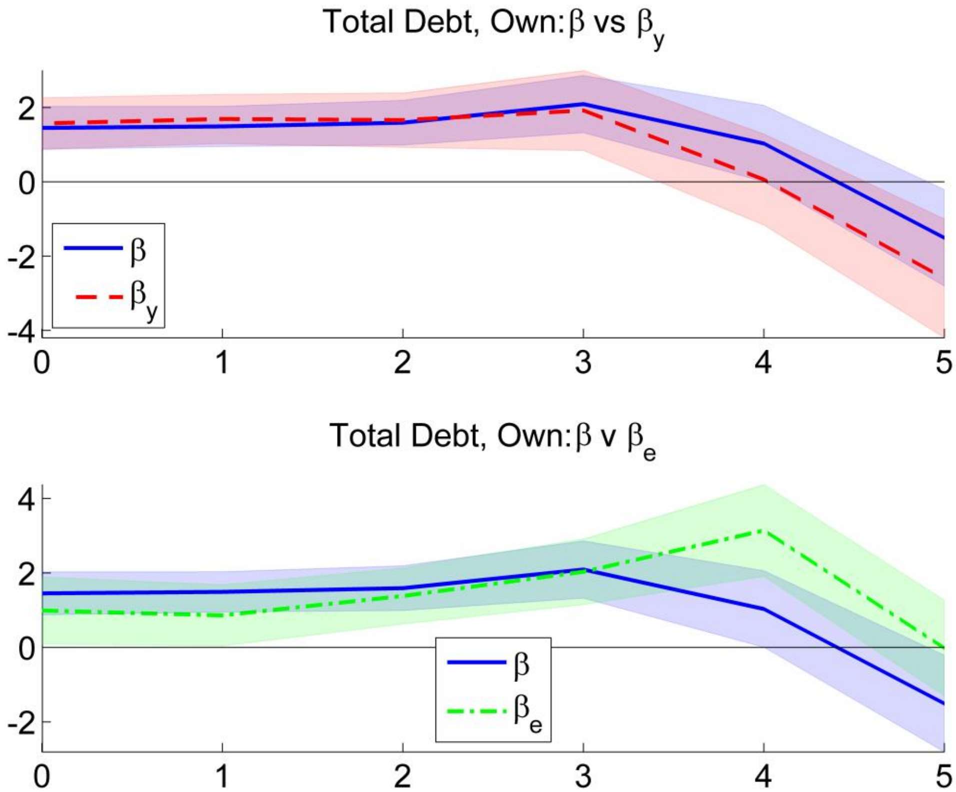

Figure 2: Coefficient estimates across different lags ±2 standard deviations for <u>total debt (owner)</u> regressions. Top panel: HPI growth (blue) vs forecast (red); bottom panel: HPI growth (blue) vs forecast error (green).

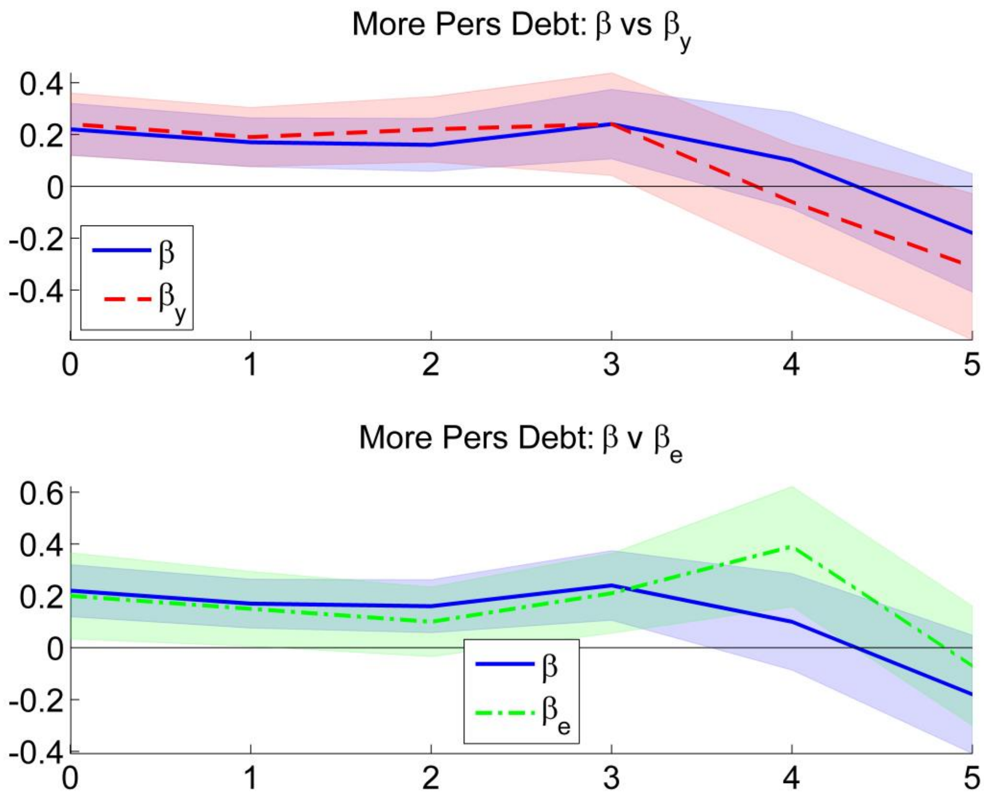

Figure 3: Coefficient estimates across different lags ±2 standard deviations for <u>more personal debt</u> regressions. Top panel: HPI growth (blue) vs forecast (red); bottom panel: HPI growth (blue) vs forecast error (green).

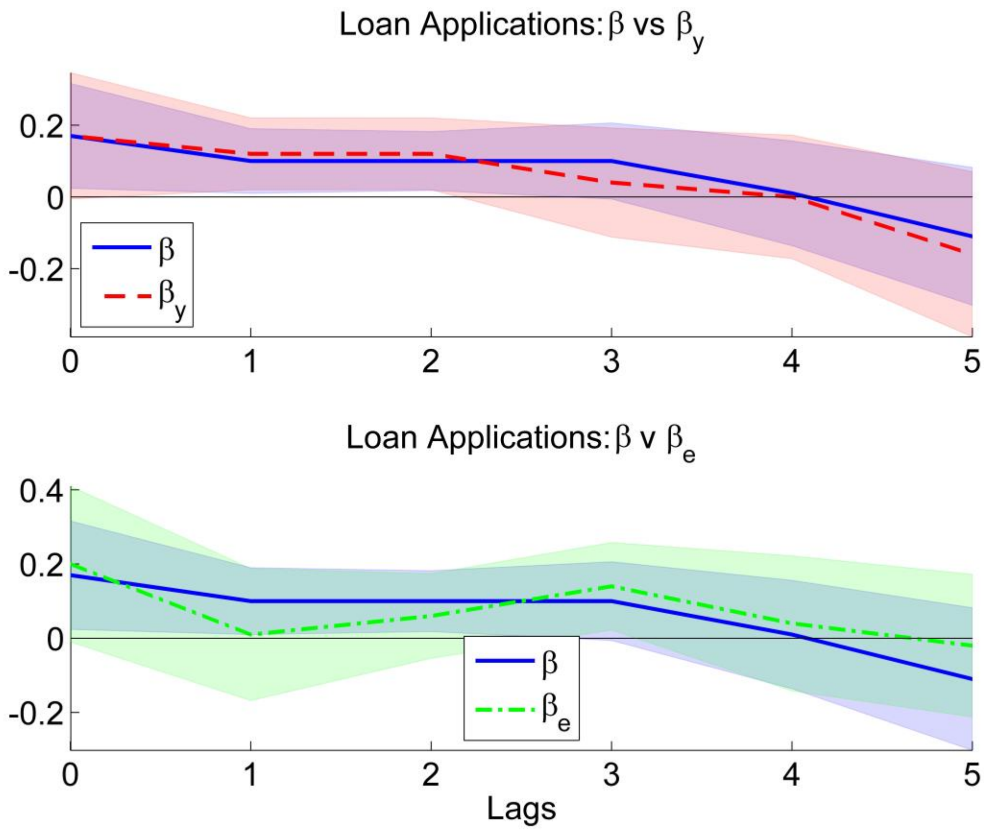

Figure 4: Coefficient estimates across different lags ±2 standard deviations for loan applications regressions. Top panel: HPI growth (blue) vs forecast (red); bottom panel: HPI growth (blue) vs forecast error (green).