How Firms Respond to Business Cycles: The Role of Firm Age and Firm Size*

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I. *Introduction*

The economic downturn of 2007-2009 is one of the two largest cyclical downturns experienced in the U.S. in the post WWII era – the other being the 1982-83 downturn. One obvious difference between these two downturns is the subsequent recoveries. Following the 1982-83 downturn, the U.S. exhibited a rapid recovery from 1984 through 1986. In contrast, the recovery from the 2007-09 downturn has been relatively anemic. In interpreting these differences, much commentary and analysis has focused on the differences in the nature of the downturns, especially focusing on the financial crisis in the most recent downturn. A critical feature of the latter is associated with the collapse in housing prices in the U.S.

To explore these issues further, we exploit a recently developed comprehensive longitudinal database of employer businesses in the U.S. that enables us to track employment dynamics by firm size, firm age and geographic location. While the basic facts mentioned above are now well known, we show with this rich new data that young and small businesses have been hit especially hard in the 2007 to 2009 recession. Businesses less than five years old and with fewer than 20 employees exhibited a decline in net employment growth from 26.6 percent to 8.6 percent from 2006 to 2009. Over this same period, businesses more than five years old with more than 500 workers exhibited a decline in net employment growth from 2.8 percent to -3.9 percent. The net growth rate differential between such young/small businesses and older/large businesses declined from 23.7 percent to 12.5 percent.

Our work is related to an ongoing debate in the literature on how firms of different sizes respond to the business cycle and financial shocks. One strand of the literature suggests small firms have a disproportionate response, relative to large firms, to financial and monetary policy shocks (Gertler and Gilchrist, 1994 and Sharpe, 1994). Chari, Christiano and Kehoe (2007) caution that the greater cyclicality of small relative to large firms is sensitive to time period and cyclical indicators. In recent work, Moscarini and Postel-Vinay (2012) document greater sensitivity of large relative to small firms to deviations of the *level* of unemployment from its (HP-filtered) trend How to reconcile these different results remains an open question– although a careful reading of the above studies suggests that at least some of the differences stem from how business cycles are measured and the role of financial market shocks relative to other shocks.

One key factor missing from much of the analysis in this literature is the distinction between firm size and firm age. Many of the hypotheses about why small firms should be more sensitive to variation to changes in credit conditions are more aptly relevant for startups and young firms. In addition, survey evidence suggests that the relevant indicators of credit conditions vary across firms by both firm size and firm age. Specifically, startups and young firms don’t have access to commercial paper corporate bonds, or even an established credit record but rather rely on personal sources of finance including home equity to establish credit lines.[1] In that respect, the pronounced variation in housing prices during the last decade is potentially especially relevant for startups and young firms.

We investigate how firms of different size and age respond to the cycle by combining data from the Census Bureau's Business Dynamics Statistics (BDS) from 1981 to 2010 with indicators of business cycle and financial market conditions. The BDS permits us to consider differential cyclical dynamics of net job creation, gross job creation and gross job destruction by firm size and firm age. We combine the BDS with standard cyclical measures such as the unemployment rate as well as indicators of financial market conditions including housing prices. Our identification strategy exploits the geographic and time variation in the BDS. One limitation of much of the existing literature on the role of either firm size or firm age is that analyses exploit relatively short time series samples with only a limited number of cyclical episodes. This hampers the ability to identify the role played by different types of shocks and the differential response to these shocks across firms. We overcome this limitation by focusing on variation across geography (U.S. states) as well as over time.

Our analysis begins by exploring correlations and simple descriptive regressions to shed new light on the role of firm size and firm age in this context. We find that the differential in the net job creation rate between young/small and large/mature businesses declines in cyclical downturns at the national and state level. By cyclical downturns, we mean periods of contraction in the economy which we measure using either increases in the unemployment rate or declines in the net employment growth rate. The data show that distinguishing between small businesses by firm age is of critical importance. That is, older, small businesses respond less to an increase in the unemployment rate than young, small businesses. This focus on firm age helps distinguish our approach from the existing literature. We also find that when housing prices decline, young, small businesses experience a much larger decline in net job creation rates than large, mature businesses.

These findings about differential responses by firm size and firm age at the state level motivate the core of our analysis. We employ a panel VAR approach using pooled state-level data across time to achieve identification with a relatively sparse number of variables, while controlling for state and year effects. The latter implies we are controlling for economy-wide factors in an unrestricted manner (i.e., not tied to any specific type of shock). The panel VAR specification includes indicators of overall state conditions (e.g., net employment growth in state or the change in the unemployment rate in the state),

[1] See evidence for the Kauffman Firm Survey, the Survey of Small Business Finance, and the Statistics of Business Owners.

housing prices in the state, and measures of the differential net growth rates across firms by firm size and firm age.

Even though the specification has a limited number of variables, it captures a rich set of factors. First, we control for unrestricted state and year effects. Second, we use a Cholesky ordering of the variables in the panel VAR to identify and estimate orthogonalized shocks in this system. The state cyclical indicator is first in the causal ordering – this yields the identification of a generic state-specific cyclical shock reflecting state-specific variation in business cycle conditions (from demand, supply or credit markets) as reflected through the state labor market. Housing prices are after the overall state cyclical indicator in the causal ordering so that the identified innovation to housing prices is orthogonal to changes in state-specific business cycle conditions. This approach makes it possible to distinguish between the impact of home price changes and labor market conditions independently of their influence on each other and of the impact of aggregate macro disturbances.

We find that an innovation to the state-specific cyclical indicator associated with a downturn (e.g., a rise in the state unemployment rate) reduces the differential in the net job creation rate between young/small and large/mature businesses and that the effect persists for a number of years. That is, the net growth rate of young/small businesses falls more in contractions than does the net growth rate of large/mature businesses. Similarly, we find that a decline in housing prices in the state yields a greater decline in the net growth rate of young/small businesses relative to the decline in growth rates at large/mature businesses. In addition, the effect is much subdued when examining the differential net job creation rate between mature/small and mature/large businesses. In this regard we find it is again critical to distinguish between young and mature small businesses.

The panel VAR results also permit us to examine the impact of shocks in specific years and states. For example, we show that the net growth differential between young/small businesses and large/mature businesses fell by about six percentage points in California from 2007 to 2009. Using the results from the panel VAR, we show that the decline in the orthogonalized housing price shock in California (which was larger than the national decline) accounts for two thirds of this decline in the net growth rate differential over this period. We find similar patterns in other states with especially large declines in housing prices, while such responses to housing prices are absent in states with little or no declines.

Our results suggest that there are a number of mechanisms that may be at work in accounting for the greater sensitivity of young and small businesses to local shocks, and local housing price shocks in particular. One of these mechanisms is a housing price/home equity financing channel that, as suggested above, is especially relevant for startups and young businesses. While more data and analysis are needed to confirm this specific channel, our results are consistent with this mechanism.

The paper proceeds as follows. The next section provides a brief background review of the literature. Section III describes the data we use for the analysis. Section IV presents basic facts and some simple descriptive regressions. The panel VAR specification is presented in Section V along with results from this analysis. Concluding remarks are in Section VI.

II. Background

As discussed in the introduction, a number of papers have assessed the differential impact of macroeconomic shocks on firms of different size. In this section, we provide more detail about the measures and methods of these papers to provide guidance and perspective for our analysis. We also tie in relevant literature discussing alternative financing options for large and small/young firms that illustrate both why small and young firms may be more credit constrained, as well how home equity helps alleviate these constraints .

Much of the literature examining the differential impact of the cycle on firms of different size investigates the financial transmission mechanism. In an influential paper, Gertler and Gilchrist (1994) assess the role of credit market frictions in propagating business cycles. Using firm size as a proxy for capital market access, the authors estimate the response of small versus large manufacturing firms to monetary policy changes while controlling for the business cycle. They find that large and small firms have similar responses to easing credit conditions; however, they show that small firms exhibit much sharper declines in sales and inventories during periods of credit market tightening relative to large firms. Chari, Christiano and Kehoe (2007) extend the Gertler and Gilchrist analysis to include three additional recessions and to compare the effects of monetary shocks and business cycle shocks as captured by NBER recession dates. Chari et al. (2007) confirm the result that small firms are more responsive to the recessions (monetary and NBER) in the original Gertler and Gilchrist timeframe. Results for the three additional recessions, however, suggest that small firms are more responsive to monetary policy shocks, while large firms are more sensitive to NBER recessions. These disparate results lead Chari et al. to conclude that there is no particular difference in the response of the sales of small establishments in recessions to generic “aggregate shocks”. The story may be more nuanced, however, since their findings are also consistent with the interpretation that different recessions, with potentially different underlying causes, affect small and large firms differently.

There is also evidence about the effects of cyclical changes on employment decisions of firms of different size. Sharpe (1994) assesses the theory that more leveraged firms will hoard labor relatively less when financial markets are tight. Using firm size as a proxy for financial vulnerability, Sharpe instruments for demand and monetary shocks with growth in industrial production and changes in the federal funds respectively. Consistent with Gertler and Gilchrist (1994), Sharpe finds that small firms are quicker to lay off workers during a recession, though not necessarily quicker to hire during an expansion.

These papers are careful in their analysis but rely on datasets that do not cover the entire U.S. economy and in some cases use measures of firm growth that may be sensitive to M&A activity.[2] In more recent work, Moscarini and Postel-Vinay (2012) use U.S. economy-wide data from the Census Bureau's Business Dynamic Statistics (BDS) database from 1979-2009 to present evidence about the connection between the level of unemployment and the difference in net job creation at large versus small firms. They obtain a correlation of -0.54 between the differential net job creation rate for large vs. small firms and the Hodrick-Prescott (HP) filtered unemployment rate.[3] Their focus on the level of unemployment is motivated by a theoretical framework in which large firms poach employees from small firms when labor markets are tight. As will become clear in our discussion below, it is important to recognize that periods of above and below trend unemployment only imperfectly correspond to cyclical contractions and expansions of economic activity. In that respect, Moscarini and Postel-Vinay are less about the behavior of large versus small firms in expansions and contractions, but rather about their behavior in periods of high and low unemployment .

Thus far, most of the literature has focused on the role of firm size and the cycle. For Moscarini and Postel-Vinay, firm size is the relevant variable from the theory. For papers addressing the role of financial frictions, firm size is often used as the proxy for differential access to credit across firms even though it is undoubtedly a limited measure. Indeed, many of the papers highlight that firm age would be a preferable proxy but firm age is less readily available. For example, Gertler and Gilchrist (1994) comment that "The informational frictions that add to the costs of external finance apply mainly to younger firms…" (p. 313). Recent work has emphasized that startups and young firms use different forms of credit than more mature businesses. For example, Mishkin (2008) and Robb and Robinson (2010) emphasize the role of home equity financing for startups and young businesses.

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[2] Sharpe (1994) uses *Compustat* data from 1959 through 1985. Gertler and Gilchrist (1994) use the *Quarterly Financial Report for Manufacturing Corporations*, from 1958:4 through 1991:1. Chari, Christiano and Kehoe (2007) extend the analysis in Gertler and Gilchrist (1994) to cover 1952:1 through 2000:3. Davis, Haltiwanger, Jarmin and Miranda (2007) show the COMPUSTAT data is not representative of the economy as a whole.

[3] Note that Moscarini and Postel-Vinay measure the net difference as the difference between large and small firms. In what follows, we use large/mature firms as the base so all of our differentials are for a group minus the large/mature firms. So in our analysis when we find a positive correlation, for example, between the net differential between old/small and large/older businesses with the unemployment rate, this is the same finding from that in Moscarini and Postel-Vinay. However, as will become clear we find the opposite pattern in our state-level analysis in response to state-specific cyclical shocks.

Despite its potential importance, we know very little about how the cycle affects firms of different ages. Recent empirical work examining the size-age growth relationship documents the need to distinguish between firm size and firm age when assessing employment changes at different types of firms. Since most firms enter at the bottom of the size distribution, firm size and age are closely related. There are many small firms, however, that are old. Haltiwanger, Jarmin and Miranda (2010) illustrate the potential omitted variables bias that can occur when estimating the effect of firm size without controlling for firm age. They confirm the conventional wisdom that small firms have higher net growth rates than large firms, but show that this relationship disappears once they control for firm age. To the extent that certain macroeconomic factors interact with firm size and age differently, estimates of the role of size will be confounded by the role of age if both variables are not included in the estimation.

There are some papers that have examined the differential cyclical dynamics of businesses by business size and business age. For example, Davis and Haltiwanger (2001) examine employment effects of oil price shocks and credit market shocks on establishments of different size and age within the manufacturing sector. The authors use a VAR approach that is similar methodologically to the approach we take in this paper. They find that industries with a large share of young, small plants are more cyclically sensitive to credit market shocks which they argue is supportive of the evidence in Gertler and Gilchrist (1994). They also find that most of the net response of young, small plants is associated with the response of job creation rather than job destruction.

Given this paper's focus on the local effects of housing price fluctuations, the more recent and influential papers by Mian and Sufi (2010, 2011, 2012) are relevant. Mian and Sufi explore the relationship between housing prices, household borrowing and local economic outcomes. Using exogenous variation in housing prices as an instrument for household borrowing, they find that highly leveraged U.S. counties in 2006 exhibited the largest decreases in consumption and increases in unemployment. In addition, because the relationship between leverage and unemployment is only present in non-tradable sectors, the authors conclude that the household borrowing channel is an important transmission mechanism that works through a consumption channel. We consider these insights in light of our evidence on the differential (local) effects of the cycle and housing prices on young and small businesses. We note, however, that the relationship Mian and Sufi document between housing prices and household balance sheets suggests that the former are an indicator of credit conditions that are especially relevant for startups and young businesses.

III. Data Sources and Measurement Methodology

To conduct the empirical investigation, we use the Census Bureau's Business Dynamic Statistics (BDS). The BDS includes measures of employment dynamics by firm size, firm age, and state as well as other employer characteristics such as industry.[4] The BDS is based on tabulations from the Longitudinal Business Database (LBD). The LBD covers the universe of establishments in the U.S. nonfarm business sector with at least one paid employee. Employment observations in the LBD are for the payroll period covering the 12th day of March in each calendar year.

Firm size measures in the LBD and BDS are based on the total employment at the enterprise or firm level. The latter is defined by operational control. We use the current average size measures from the BDS (although we show that for our current analysis results are robust to using initial size).[5] This is the preferred approach to abstracting from regression to the mean issues as described in Davis et al. (1996). Current average firm size is the average of firm size in year *t-1* and year *t*. Firm age in the BDS is based on the age of the oldest establishment of the firm when the firm is created. For firm startups with all new establishments firm age is set equal to zero. For firms that are newly created as part of M&A, ownership change or some other form of organizational change, the firm age is initiated at the age of the oldest establishment. From that point forward, the firm ages naturally as long as it exists.[6] A strength of the BDS firm size and age measures is that they are robust to ownership changes. For a pure ownership change with no change in activity, there will be no spurious changes in firm size or firm age. When there are mergers, acquisitions, or divestitures, firm age will reflect the age of the appropriate components of the firm. Firm size will change but in a manner also consistent with the change in the scope of activity. For further discussion on how our measurement methodology yields patterns of the relationship between net growth, firm size and firm age that are robust to ownership changes and M&A activity see Haltiwanger, Jarmin and Miranda (2010). Critically, for every establishment in the LBD,we assign the establishment to a given firm size and firm age class in each year.

To simplify the analysis we consider broad firm size and broad firm age groups. Specifically, we consider two firm age groups: firms less than five years old and firms five years old or older. In what follows, we refer to these two groups as young and mature (or sometimes young/older). Using these firm age groups permits us to track employment dynamics in the BDS at the national and state level in a

[4] The BDS is built up from establishment-level data so we know the detailed geographic location of economic activity. The firm characteristics are based on the national firm but the state-level activity is for all establishments in that state in the given firm size and firm age group.

[5] For a detailed description of differences between this and other sizing methodologies see Haltiwanger, Jarmin and Miranda (2010). We include some analysis below and in the appendix using firm size groups defined by initial size. Our results are robust to using this alternative.

[6] If the age composition of establishments in the firm change due to M&A this does not change firm age.

consistent manner from 1981 to 2010. For firm size groups, we consider three groups: less than 20, 20-499 and 500+. In what follows we refer to these groups as small, medium and large. While Haltiwanger, Jarmin, and Miranda (2010) consider finer age and size categories, the focus here on assessing how age and size affect cyclical behavior limits the number of groups that can be studied. In addition, the groups here represent much finer categories than those used in most of the existing work.

The use of broad size and age classifications for studying cyclical dynamics is very much in the spirit of Davis and Haltiwanger (2001) and Moscarini and Postel-Vinay (2012). As we discuss in greater detail in the measurement appendix, the net growth rate for a given broad size and age class "s" is given by:

$$g_{st} = \frac{E_{st} - E_{st-1}}{X_{st}}$$

where $E_{st}$is employment for cell "s" in period t, and $X_{st} = 0.5 * (E_{st} + E_{st-1})$.[7] In measuring and defining E_{st-1} it is critical to emphasize that this is the employment in period t-1 of the establishments that are in cell "s" in period t. That is, the above is consistent with:

$$g_{st} = \sum_{e \in s} \frac{X_{est}}{X_{st}} \left(\frac{E_{est} - E_{est-1}}{X_{est}} \right) = \sum_{e \in s} \frac{X_{est}}{X_{st}} g_{est}$$

where "e" indexes establishments. The critical point is that we are tracking a given set of establishments classified into cell "s" between t-1 and t which obviously requires longitudinal establishment-level data. That is, there are no reclassifications of establishments between t-1 and t for the measurement of $E_{st}$and E_{st-1}.[8] Another critical issue is that $E_{st}$and E_{st-1} includes the contribution of establishment entry and exit.

The age categories we use group the contribution of firm startups with other young businesses. While distinguishing the role of startups has evident appeal, Haltiwanger, Jarmin and Miranda (2010) show that young firms exhibit a rich "up or out" dynamic – with most startups failing in their first five years but otherwise showing considerable average growth conditional on survival. Thus, our grouping is a way to capture the overall contribution of startups and this up or out dynamic for young firms within

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[7] This measure of net growth is bounded between (-2,2) and is symmetric around zero. Its desirable properties are discussed extensively in Davis, Haltiwanger, and Schuh (1996).
[8] Note that the level of aggregation "s" that we consider, it is not critical we use the DHS net growth rate at the cell level (e.g., the log difference of $E_{st}$and E_{st-1} yields very similar growth rates as the DHS net growth rate at this level of aggregation – this is not surprising since the DHS net growth rate is a second order approximation to the log first difference). The advantage of the DHS net growth rate approach is the establishment entry and exit are readily integrated into the net growth rate measures.

one category. Of course, this example and discussion highlights that it is of interest to break out the components of the net growth rate of the cell into margins of expansion and contraction of establishments. For that purpose, we consider analysis that distinguishes between the job creation and job destruction margins below.[9]

It is also useful to relate the cell-based net growth rates to the aggregate as shown by:

$$g_t = \sum_s \frac{X_{st}}{X_t} g_{st}$$

As will become clear in the next section, most of the cyclicality of the aggregate net growth rate reflects the cyclicality within broad size and age class cells rather than changes in the shares at business cycle frequencies.

We supplement our BDS measures of employment dynamics with a variety of business cycle and financial market indicators. At the national and state level, we use unemployment rates from the BLS, real housing prices from the Federal Housing Finance Agency (FHFA), and growth rates in real GDP and real Personal Income from BEA.[10] Housing prices at the national and state level are endogenous, reflecting many factors. Our panel VAR approach is designed to address these issues. For some of our national descriptive analysis, we also use an indicator of interest rate spreads. Interest rate spreads have often been used as an indicator of changes in the risk and liquidity of credit markets (see, Krainer (2004) and Mueller (2009) for empirical applications and Bernanke and Gertler (1989) and Bernanke, Gertler, and Gilchrist (1999) for underlying theory connecting credit spreads and real activity). For this purpose, we use the spread between Moody's AAA Corporate Yield and the Merrill Lynch High Yield Red 100.[11] Details of the measurement of these variables are in the appendix.

When integrating the data across the different sources, we pay careful attention to the timing of the observations. Employment observations in the LBD/BDS are for the payroll period covering the 12th day of March in each calendar year.   We measure all of our other variables over the same March-to-March horizon (see the appendix for details).

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[9] The measurement appendix includes discussion and formulas that show how net and gross job flow rates are calculated for size and age groups.

[10] Real GDP at the quarterly level is available at the national level so we construct annual averages using the re-timed. At the state level, real GDP can be constructed on an annual basis, but not for the properly re-timed year. We use the re-timed state GDP for robustness purposes, but note that it is off by quarter. We therefore also use real personal income at the state level which we can construct for the re-timed year. Additional details are in the appendix.

[11] We use the HP filtered spread variable.

IV. Basic Facts About Cyclicality by Firm Size and Firm Age

A. National Patterns

Figure 1 shows the share of employment by firm size and firm age from 1981-2008. Even though most firms are small (about 35 percent of firms are young/small and about 50 percent are mature/small), most employment is accounted for by large/mature firms. The share of employment at large/mature firms has risen over the last 30 years while the share of young/small and young/medium firms has noticeably fallen. As described in Decker et. al. (2012), this is associated with a secular decline in the firm entry rate over this period of time. Figure 1 also shows that the share of employment in young/large firms, those less than five years old and with more than 500 employees, is very small – less than one percent. In what follows, we exclude the young/large firm group from the analysis since they account for such little economic activity. Note that while there are some secular trends in Figure 1, the shares are relatively stable over the cycle. The aggregate net employment growth rate is, by construction, the employment share weighted average of the net employment growth rates by firm size and firm age group. Since the shares are relatively stable over time, the fluctuation in the aggregate must be driven by within firm size and firm age group variation in growth rates to which we now turn.

Figure 2 shows net growth rates by firm size and age groups. It is evident that net employment growth rates are highest for young, small and young, medium firms. Net employment growth rates are lowest for older, small firms. These first two points echo the findings in Haltiwanger, Jarmin and Miranda (2010). All groups exhibit evident cyclicality but it appears that the nature of this cyclicality has varied over time. For example, net job creation rates for young/small firms and young/medium firms declined sharply in the Great Recession. The decline in this recession is much larger than in any of the other recessions since 1981. It is also evident that large/older firms are quite cyclical. Overall, we also note that there are no apparent trends in the net growth rates. In this respect, we note that the declining trends in overall net growth observed in the US economy are driven more by changing shares of firm size and age than within firm size and age net growth rates.

To help put the patterns of Figure 2 into perspective, Table 1 presents simple descriptive regressions relating the net growth rate for the overall economy by firm size and firm age group with the change in the national unemployment rate, the interest spread variable discussed in the prior section, and the growth rate in real housing prices. No causal inferences can be drawn from these regressions but the implied partial correlations are of interest. We find that the overall net growth rate series and the net growth series for every firm size and firm age group are inversely correlated with the change in the unemployment rate. We find that the magnitude of the estimated coefficients with respect to the change in the unemployment rate varies substantially across groups. The largest (in magnitude) coefficient is for the young/small while the smallest coefficient is for the older/small group. Taken at face value, this suggests that the young/small are the most cyclical and the old/small are the least cyclical. We also find that holding the unemployment change and housing prices constant, there is an inverse relationship between the interest rate spread and net growth rates overall and for each group. Here we find the largest effects for medium and large firms consistent with the idea that these firms are the most likely to access external finance through corporate bond markets.[12] Finally, holding unemployment and the interest rate spread constant, we find a positive relationship between housing price growth and net growth rates for all groups with the largest coefficients for young businesses (small and medium) consistent with findings that smaller firms are more likely to collateralize their loans using real estate assets.[13] We show in appendix Table A.1 that we obtain very similar results using growth rates in real GDP as the cyclical indicator.

Figure 2 and Table 1 are suggestive that there are differential cyclical patterns across firm size and firm age groups. It is such differences that are the focus of the remainder of our analysis. For this purpose, we follow Moscarini and Postel-Vinay (2012) by focusing on net growth rate differentials across firm size groups but extend the approach to also include firm age. We focus on five size-age groups rather than the two size groups (small and large) employed by Moscarini and Postel-Vinay. As such, we use large/older firms as the base group and focus on net differentials for each of the other four groups with respect to this base group. Figure 3 presents these net growth rate differentials. It is evident that the net differential for the young/small group relative to the large/mature and the young/medium group relative to the large/mature group fell substantially in the Great Recession. This pattern is consistent with the simple descriptive regressions in Table 1.

To help provide more perspective on the patterns in Figure 3, Table 2 presents simple correlations of the net differentials of employment growth rates with alternative cyclical indicators. We use differential growth rates since they highlight variation in different groups' responses most clearly. Our preferred cyclical indicators are indicators reflecting growth or change – that is indicators about whether the economy is expanding or contracting. As such, our preferred indicators are the change in the unemployment rate, the net growth rate of private sector employment, or the growth rate in real GDP. We prefer these indicators for a number of reasons. Growth and change indicators are inherently more tied to NBER business cycle turning points since growth measures play a critical role in the determination of such turning points. In addition, and likely as importantly in our analysis, we need our cyclical

[12] See Fazzari and Hubbard (1988) and Robb and Walken, 2002 for evidence on financing sources of small and large business.
[13] See Mishkin, 2008, and Mach and Wolken, 2006

indicator to be closely related to the changes in business conditions that influence key variables such as interest rates and housing prices. In the VAR analysis that follows, we will use a cyclical indicator as a way to capture unobserved demand, supply and credit factors that in turn may influence housing prices. In the national data, the correlation between real housing price growth and the change in unemployment rate is -0.56, the correlation between real housing price growth and net employment growth is 0.55 and the analogous correlation between real housing price growth and real GDP is 0.57.

Moscarini and Postel-Vinay (2012) focus on an alternative indicator of the state of the economy – the deviation of the unemployment rate from the (Hodrick-Prescott) trend. Their motivation is based on a theoretical model of poaching in the labor market. They argue that large firms are more likely to poach workers from small firms in times when unemployment is below trend. The latter is not our focus but given that their work and ours is about differential net responses of firms by firm size (and in our case firm age) it is useful to consider their indicator as an alternative. Table 2 includes the latter for completeness. The HP filtered unemployment rate in the national data has quite different properties than the cyclical indicators of expansion and contraction. This can be understood by considering the simple correlations of the alternative indicators. Over our sample period the correlation between the change in the unemployment rate and the net employment growth rate is -0.84 while the correlation between the net employment growth rate and real GDP growth is 0.90 . The correlation between the net employment growth rate and the HP filtered unemployment rate is only -0.23, the correlation between the change in the unemployment rate and the HP filtered unemployment rate is 0.56, and the correlation between the growth rate of real GDP and the HP filtered unemployment rate is -0.37. Most importantly for our VAR analysis, the correlation between housing price growth and the HP filtered unemployment rate is -0.10 in the national data. From that perspective, the HP filtered unemployment rate has limitations in terms of reflecting cyclical shocks that impact both housing prices and changes in the level of economic activity.

Table 2 presents the correlations for two periods: 1981-2010 and 1981-2006. For the entire sample period, we find a negative and significant correlation between the net differential for young/small with the change in the unemployment rate. Similarly, we find a positive and significant correlation between the net differential for young/small and the net employment growth rate as well as the real GDP growth rate. Similar patterns are also observed for young/medium businesses although the magnitudes of the correlations are somewhat smaller. For both young/small and young/medium, the correlations are the same sign but are reduced substantially when the post-2006 data are excluded.

For the older/small and the older/medium, less systematic patterns are observed with respect to correlations with cyclical indicators of change and growth. The older/small differential has a positive and insignificant correlation with the change in unemployment rate, a positive but insignificant correlation with the net employment growth rate and a negative but insignificant correlation with the Real GDP growth rate. The older/medium differential has a negative and insignificant correlation with the change in unemployment rate, a positive and significant correlation with the net employment growth rate, and a positive and marginally significant correlation with the Real GDP growth rate. When we exclude the post-2006 period, the correlations for the older/small and older/medium all move in the direction of less cyclicality of these groups relative to older/large firms.

The last panel on the right shows the patterns for the HP filtered unemployment rate. For young/small and young/medium differentials, there are no statistically significant patterns in either sub-period. For the older/small and older/medium differentials we find, consistent with the patterns highlighted by Moscarini and Postel-Vinay (2012), a positive and significant correlation for the overall sample period and the sub-period with post-2006 data excluded.[14] Relative to their finding at this level of aggregation, our results highlight that their finding of the greater sensitivity of large firms relative to small firms with respect to deviations in the level of unemployment is being driven by mature firms. In contrast, the effect they emphasize is smaller in magnitude and insignificant for young/small firms.[15]

What should we make of the varying patterns in Table 2? Perhaps the main conclusion is that statistical inference about the cyclical patterns of net differentials is difficult with only 30 observations. As Table 1 shows, all firm size and firm age groups exhibit pronounced cyclicality but measuring the differential response with only 30 observations is difficult. The results in Table 2 are sensitive to both the

[14] Moscarini and Postel-Vinay (2011) also note that their result is only robust to considering cyclical indicators based on deviations from trend and not robust to using cyclical indicators of expansions or contractions. We find that when the latter indicators are used, young/small and young/medium businesses are more cyclically responsive than older/large businesses. Moscarini and Postel-Vinay (2012) use initial firm size to classify firms in their analysis. In Appendix Table A.2, we show the results of Table 2 are robust to this alternative so this is not driving differences. Moreover, in Appendix Table A.5 we show that the state by year patterns emphasized in our analysis are robust to using initial firm size to classify firms. We also show in Appendix Figure A.1.7 that the impulse responses to state-specific cyclical and housing price shocks are robust to using initial size to classify firms.

[15] One way to emphasize that there is an inherent difference between considering firm size and firm age effects is simply to consider correlations where one focuses on only firm age effects and those where one only focuses on firm size effects. We find that if we use only firm age and consider two age groups where young is <5 and mature is 5+ that the correlation between the change in unemployment rate and the net differential between young and mature is -0.65 (and significant). In contrast, if we only consider firm size with two size groups where small/medium is <500 and large is 500+ (and to be similar to Moscarini and Postel-Vinay use initial size classification) then the correlation between the change in the unemployment rate and the net differential between small/medium and large is -0.26 and not significant. Turning to the indicator used by Moscarini and Postel-Vinay we find that the latter correlation is 0.36 and significant. The latter differs some from the correlation emphasized by Moscarini and Postel-Vinay (recall they have the opposite sign convention and so this is equivalent to a -0.36 correlation with their sign convention). We find that this is associated, at least in part, with the specific time series sample. That is, if we use the 1981-2009 sample (closer to what Moscarini and Postel-Vinay use) we obtain a correlation between the HP filtered unemployment rate and the net differential between *small and large* of 0.54 which is very similar to their highlighted correlation. So even adding/subtracting one year alters this correlation non-trivially.

sample period as well as to the indicator. For the latter, as we have noted, we have a preference for cyclical indicators that track expansions and contractions. The second conclusion from Tables 1 and 2 is that, at least suggestively, distinguishing between young/small and older/small matters. Uniformly in Tables 1 and 2, young/small firms are more cyclically sensitive than older/small firms. But given the limitations of analysis with only 30 observations, in subsequent sections we focus on our attention on variation not only across time but across geography.

Before turning to the state-level patterns, we consider how the patterns in Figure 3 vary by the job creation and job destruction margins. Figure 4.a shows the job creation patterns while Figure 4.b shows the job destruction patterns. Figure 4.a shows that the job creation for small/young fell substantially in the 2007-09 recession. But Figure 4.b shows also that the job destruction for small/young rose substantially over this same period of time. For both job creation and destruction margins, young/small exhibited more variation over this period than old/large. The implication is that at least part of the story for why net differentials for young/small fell so much in this period must be associated with the rise in job destruction for incumbent young/small firms.[16]

B. State-level Patterns

Table 3 shows simple descriptive regressions at the state-level. We control for both state effects and year effects in virtually all of our analysis at the state-level. The state effects control for any time invariant state-specific factors, while the year effects control for any common (economy-wide) factors in an unrestricted manner in each year. As such, for our state-level analysis, cyclical indicators and shocks should be interpreted as reflecting state-specific variation. We return to the relevance of this point in our discussion of the panel VAR analysis in the next section.

The top panel shows bivariate regressions relating the change in unemployment at the state level with the differences in net growth rates at the state level across firm size and firm age groups. All of the differences are expressed as differences with Older/Large group. The top panel shows that all net growth differentials relative to large/older businesses decrease when unemployment rises. The largest decrease is for young/small and young/medium businesses. The estimated coefficient for young/small is more than four times as large as the coefficient for older/small. All of these effects are statistically significant at the one percent level.

[16] In unreported results, we have found that the job creation and job destruction patterns reflect consistent movements in the underlying components of job creation from continuers, job creation from entry, job destruction from continuers and job destruction from exit. That is, all margins contribute to the patterns.

The lower panel includes as an additional regressor state-level real housing price growth rates. In terms of the cyclicality indicator (the change in the unemployment rate), the quantitative and qualitative patterns are about the same as in the upper panel. In terms of housing prices, we find that an increase in housing prices is associated with a disproportionate response of the younger and smaller businesses relative to older/larger businesses. This is true for all groups but is especially true for the young/small group and interestingly the older/small group. Being very small makes one more responsive to housing prices regardless of age. All of the estimated effects are statistically significant.

We also show in the appendix that the patterns in Table 3 are robust to using alternative cyclical indicators for change and growth including the net employment growth rate, the growth rate in Real GDP and the growth rate in Real Personal Income (see appendix Tables A.3, A.6 and A.7).[17] In the prior section, we noted that the national patterns are sensitive to whether the cyclical indicator is based on a measure of change or growth vs. deviations of levels from trend. Table 4 shows that the patterns in Table 3 are robust to using the HP-filtered unemployment rate at the state level. That is, Table 4 shows that the net differential between young/small businesses and large/older businesses narrows when the unemployment rate in the state is above trend. Moreover, like the results in Table 3, we find that older/small businesses are less cyclically sensitive than young/small businesses as the coefficients are substantially smaller in magnitude for the older/small businesses. But we find that older/small businesses respond more to the state-specific component of this indicator than to large/older businesses (although the estimate for the old/small differential is only significantly different from zero at the 10% level). We also find that the relationship between net differentials and housing prices is robust to the use of alternative indicators.

The results at the state-level using the HP-filtered unemployment rates raise some questions about the findings and interpretation of Moscarini and Postel-Vinay. Their primary result is that large businesses exhibit a greater decline in net employment when unemployment is above the (HP-filtered) trend. They interpret this as being consistent with a theoretical model where large businesses are more likely to poach workers from small firms when unemployment is low. Our results show that their finding does not hold using state-level variation when we control for state and year effects.[18] Presumably the

[17] We also show in Table A.5 that the results in Table 3 are robust to using initial size.

[18] We note that Moscarini and Postel-Vinay (2012) also consider state-level variation. Unlike our analysis, they did not control for state and year effects. We show in Table A.4 that the results in Table 3 using the change in the unemployment rate are robust to not controlling for year effects for young/small and young/medium net differentials. However, in Table A.4 we find that estimated effect for the old/small differential with old/large turns positive and significant when controlling only for state fixed effects. Moreover, in unreported results, we find that when we don’t control for year effects but do control for state effects and use the HP filtered unemployment rate that we obtain the Moscarini and Postel-Vinay result for old/small net differentials with large/old businesses but don’t

poaching by large firms should be as responsive to state-specific deviations from trend as national deviations. We leave further investigation of these issues to future work. For our purposes, we note that our findings are robust to alternative cyclical indicators at the state-level but we still prefer cyclical indicators based on growth and change given that such indicators will capture the unobserved cyclical shocks we seek to control for in our panel VAR in the next section.

The descriptive evidence in the prior section shows that the national patterns are sensitive to inclusion of the post-2006 period. This is not surprising given Figure 1 which highlights that young/small businesses experienced an especially large decline in the Great Recession. Table 5 reports results from the same exercise as Table 3 but excluding the post-2006 data. We find results that are very similar to those in Table 3. There is sufficient state-specific variation that the patterns are robust to excluding the recent period.

Whether at the national or state level, the patterns described in this section are only correlations or partial correlations so no causal inferences can be made. In the next section, we exploit the rich joint variation across time and geography in a more structured analysis.

V. Panel VAR Analysis

A. Specification

We now turn to a panel VAR analysis. The specification we consider has the following form:

$$Y_{s,t} = A(L)Y_{st} + State_s + Year_t + \varepsilon_{st}$$

where Y is a vector of covariates, L is a lag operator of length L, and A(L) a matrix of lagged coefficients, State and Year represent state fixed and year fixed effects and ε_{st} is the residual innovation vector of shocks to each of the covariates. Identification is achieved both by taking into account lags (A(L)) but also by specifying a relationship between the reduced form innovations ε_{st} and structural innovations. That is, after absorbing the state and year effects we can invert the AR representation to form the MA representation given by:

$$\hat{Y}_{s,t} = D(L)\varepsilon_{st} = B(L)\eta_{st}$$

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find their result for small/young net differentials. Thus, our findings suggest that their results are being driven by old/small businesses relative to old/small and by aggregate variation in their measure and not by state-specific variation in their measure. We also note that in all of these alternative specifications, we always find that young/small businesses are more sensitive to housing price shocks. We find this for the descriptive regressions as well as the panel VAR analysis regardless of the cyclical indicator we use.

where t $\widehat{Y}$ is the variation in Y after absorbing the state and year effects, D(L) are the MA coefficients from inverting the AR representation, and η_{st} represents the innovations to each of the orthogonalized "structural" shocks after making some identifying assumptions. The relationship between D(L) and B(L) can be specified by: $B(L) = B_o D(L)$ where B_o represents the short run identifying assumptions. We note that in estimating the panel VAR we follow the approach developed by Holtz-Eakin et. al. (1988).[19]

For our purposes, we specify Y={Change in State-Level Unemployment Rate, State-level Housing Price Growth, Net Growth Differential Young/Small-Older/Large, Net Growth Differential Young/Medium-Older/Large, Net Growth Differential Older/Small-Older/Large and Net Growth Differential Older/Medium-Older/Large}. For identification, we use a simple lower triangular matrix for B_o – i.e., we use a Cholesky causal ordering. In the appendix, we show that all of our results are robust to using alternative cyclical indicators as the first variable in the system including the net employment growth rate, the Real GDP growth rate, the Real Personal Income growth rate and the HP-filtered unemployment rate.[20]

Our identification strategy recognizes that many factors drive state-level variation. We address this is several ways. First, we control for state and year effects. The year effects control for economy-wide factors in an unrestricted fashion. In this context, they control for economy-wide aggregate shocks from demand, supply or credit conditions. Second, we put the change in unemployment rate at the state-level first in the causal ordering. Our interpretation of the shock that emerges is that this is an innovation to a generic state-specific cyclical shock. In that respect, this shock captures unobserved state-specific demand, supply and other shocks that affect general business conditions in the state (including general credit conditions). State-level housing price growth is next in the system. The innovation here does not reflect national housing price variation given the year effects. Nor does the innovation here reflect general business conditions in the state – the impact of the latter is accounted for by the Cholesky causal ordering. In other words, when general business conditions decline in a state and housing prices decline endogenously as a result, this identification strategy controls for such variation.

Since the housing price shock we identify is orthogonal to the local unemployment rate, it does not reflect changes in general business conditions in the state. Instead, the orthogonalized housing price shock

[19] We thank Inessa Love for her STATA code (pvar.ado) to implement a panel VAR procedure in STATA. We have modified the code for our application (code available upon request). Consistent with Love and Zicchino (2006) (building on the insights of Arellano and Bover (1995)) we use the Helmert transformation to control for state fixed effects. This forward differencing procedure overcomes the problem that fixed effects and lagged dependent variables are inherently correlated.

[20] The results using the net employment growth rate are in Figures A.1.1-A.1.3, for the HP filtered unemployment rate in Figures A.1.4-A.1.5, for real GDP growth in A.1.12-A.1.14 and for real Personal Income in A.1.15-A.1.17.

may stem from supply or demand factors affecting housing prices that again are not associated with general business conditions. Mian and Sufi (2011) emphasize the role of geographic variation in household leverage as being important in accounting for geographic variation in housing price declines. Their characterization seems relevant in this case since they highlight that this geographic variation in leverage is being driven by changes in home equity values.[21] Moreover, their identification approach using the Saiz (2010) housing supply elasticity suggests that there is variation in housing prices across areas due to factors that may not be fully accounted for by local cyclical shocks.

We focus our attention on these first two "structural" shocks: unobserved state-specific cyclical shock and the state-specific housing price growth shock. We are agnostic about the causal ordering of the remaining variables in the system. Their ordering has no impact on the impulse response functions for the first two shocks of interest. We note all of the remaining variables are net differentials. By construction, the VAR is permitting such net differentials to impact all of the variables in the system with a lag. But we do not permit the net differential shocks to affect the change in the unemployment rate or housing price growth contemporaneously. The remaining shocks are interpretable as shocks to the relative outcomes across firm size and firm age groups. In principle, investigation of the properties and consequences of such shocks might be of interest but we leave that for future work. In the appendix we show results for the specification in which housing prices are last in the system.[22] Many of the effects we identify in the main text hold in this alternative specification, but we note that this ordering rules out any contemporaneous impact of housing price shocks on the net growth rate differentials. In our view, the primary concern about housing prices is that they are endogenous with respect to the economic conditions at the national and state-level. By including year effects and putting housing prices second in the causal ordering we have taken such effects into account.[23]

B. Results on Net Differentials at the State-Level

Figures 5.1-Figure 5.4 report the impulse response functions from the panel VAR in terms of responses to the unobserved state-specific cyclical shock (that reflects the innovation to the change in unemployment) and the state-specific housing price growth shock.[24] Figure 5.1 shows the response of housing prices to these two shocks. The left panel shows the response to the state-specific cyclical shock and the right panel the response to the housing price shock. As expected, we find that an innovation to

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[21] Their approach to identification is to instrument the local leverage ratio with the housing supply elasticity from Saiz (2010). Our approach is to use the panel VAR with the Cholesky decomposition to identify a housing price shock that is orthogonal to general business conditions in the state.
[22] See Figures A.1.6.a and A.1.6.b.
[23] We also note that examination of the impulse response functions with respect to these net differential shocks shows only modest dynamic impact on the change in unemployment and housing price growth.
[24] All figures include 95 percent confidence bands.

the state-specific cyclical shock yields a decline in housing prices. A one standard deviation shock yields a decline in housing prices immediately with the peak effect in 3 years. While housing prices exhibit variation consistent with being endogenous to state-specific cyclical shocks, the right panel shows that there is substantial residual variation in housing prices. The right panel shows that a housing price innovation generates a persistent increase in housing prices.

Turning to the primary effects of interest, we find in Figure 5.2 that the state-specific cyclical shock yields a decline in the net differential between young/small and large/old. The effect is largest on impact but persists for a number of years. These findings echo the basic results in the prior section. In a state-specific cyclical downturn, the differential between young/small and large/old narrows. Turning to housing prices, we find that a housing price innovation widens the net differential between young/small and large/old. Put in terms of a decline, a decrease in housing prices narrows the net differential growth rate between young/small and large/old. The effects in the right panel of Figure 5.2 are changes over and above changes from the unobserved cyclical shock. That is, the right panel reflects responses to the orthogonalized housing price shock.

Figures 5.3 through 5.5, show similar qualitative patterns for the remaining net differentials. That is, for young/medium, small/old, and small/medium we find the net differential with large/old tends to narrow during the cyclical downturns in the state. However, the magnitude of the effects varies systematically across these groups. The largest effect is for the young/small followed by the young/medium. The smallest effects are for the old/small and old/medium. In other words, it is especially the young (whether small or medium) that are responding to the cyclical shock. Similar remarks apply to the housing price innovations. This is consistent with the idea that, on average, young firms are a particularly vulnerable population of businesses. For all groups, housing price innovations tend to (at least on impact) increase the differential with the base group – the large/old firms. But again the largest quantitative effects are for the young/small and young/medium.[25]

Our findings indicate that young/small businesses are the most cyclically sensitive to generic cyclical shocks as well housing price shocks. The reported impulse response functions show the response to one standard deviation shocks from the pooled state by year data. We know that there are some years

[25] We show in Appendix Figure A.1.10 that we obtain our main results if we focus only on firm age (ignoring firm size) so that we focus on the net differential between young and mature. In Appendix Figure A.1.11, we show that if we instead had focused on firm size only (ignoring firm age) we would obtain substantially mitigated effects of both the local cyclical shock and the local housing price shock. These results are a way of emphasizing that the critical factor for obtaining our results is to distinguish across firms by firm age and not firm size. A simple way of thinking about this and consistent with the results throughout the paper is that young firms are small and medium size (essentially no young/large firms) while small firms are both young and mature. The results throughout the paper show that old/small firms behave quite differently than young/small and young/medium firms.

and some states with especially large variation in housing prices. To see this, Figure 6 shows the real housing price change in years 1981-2010 at the national level and in three different states: California (CA), Florida (FL) and North Dakota (ND). As is well-known, housing prices rose rapidly in the post-2000 period especially in CA and FL and then plummeted in the Great Recession, especially in some states such as CA and FL. In contrast, ND exhibited much milder fluctuations in housing prices. We can use the results from the panel VAR to quantify the impact of such different patterns of housing price changes on the net growth rate differentials that are the focus of this study.

Figure 7 presents the results from such an exercise. First, observe that the actual change in the differential between small/young and large/old fell substantially from 2007-09 in CA and FL but actually rose over this same period in ND. For example, in CA the differential fell from 0.18 to 0.12 over this period. Using the impulse response function (IRF) from Figure 5.2 along with the estimated structural housing price innovations from the panel VAR for these years and for these states, we can generate the responses to state specific innovations in housing prices. We do that in the Figure 7 with the bar labeled "Due to Housing Price Changes". In CA and FL, the state-specific housing price declines account for a substantial fraction (about two thirds) of the observed decline in the differential. Interestingly, the state-specific housing price increase in ND helps account for the observed increase in the differential (about one third). Note that by state-specific increase this refers to the housing price change effectively deviated from the national change since we have controlled for common year effects.

While this exercise suggests a potentially important role of state-specific housing price changes, such effects are only part of the story even for the 2007-09 period. We deliberately selected states with large deviations in housing price growth from the national trends in Figures 6 and 7. Other states also exhibited changes in the net differential between small/young and large/mature over this period without large deviations in housing price changes from the national average. By construction many other factors play a role here – the year effects that we swept out account for any common factors driving the net differentials. Moreover, state-specific changes in the general business conditions as captured by the first shock in the panel VAR are at work.

C. The Job Creation and Destruction Margins

To provide some further insights into our findings, we consider alternative specifications that focus separately on the job creation and job destruction margins. To do so, we estimate a panel VAR with the same first two variables (change in unemployment, growth in housing prices) but for the differentials consider in turn the job creation differentials in one specification and the job destruction differentials in another.[26]

For the sake of brevity, we focus on the differentials for young/small vs. old/large and the response of these differentials to the state-specific cyclical shock and state-specific (orthogonalized) housing price growth shock.[27] Figure 8.a shows the response of the job creation differentials to these shocks while Figure 8.b shows the response of the job destruction differentials. We find that the job creation differential between young/small and old/large falls when unemployment rises and housing prices fall. We find that the job destruction differential between young/small and old/large rises when unemployment rises and housing prices fall. Net growth is by construction equal to job creation minus job destruction (recall the sign convention here) so one can relate these findings to those in Figure 5.2 that show the net differential responses for these same groups. The magnitude of the responses is larger on the job creation margin relative to the job destruction margin. Still, the job destruction margin contributes substantially to the overall net response. Roughly 40 percent of the net differential response to the state-specific cyclical shock can be attributed to the job destruction margin. Moreover, the job destruction margin is the primary reason that the response to housing prices persists and is larger at one lag as opposed to the impact effect.

These patterns indicate that one should not interpret the effects for young/small firms as only reflecting the responsiveness of startups, but rather the young/small firms effects reflect the combined contribution on startups, job creation of incumbent young/small firms and job destruction of incumbent young/small firms.

D. Results by Sector

The focus of this analysis has been on the differential response to cyclical and housing price shocks by firm size and firm age. Variation by firm size and firm age may reflect many factors. One factor may be variation within and between industries. Different industries use different technologies and business models that translate into well-known differences in the firm size and firm age distributions across industries. It may be, for example, that our findings are related to differential responses across as well as within industries at the national or local level. The findings in Mian and Sufi (2012) suggest one possible

[26] Given that the differentials vary across specifications, one concern in comparing results across specifications might be that the identified state cyclical shocks and housing price shocks and their respective dynamics vary across specifications. In practice, each of these specifications (using alternatively net differentials, job creation differentials, and job destruction differentials) yields very similar state specific cyclical shocks and state specific housing price growth shocks.

[27] Figures A.1.8 and A.1.9 show the differential job creation and job destruction responses for young/medium firms. The patterns are qualitatively similar to those in Figures 8.a and 8.b.

linkage. They find that non-tradables employment is much more sensitive to the type of local cyclical shocks that we have been exploring (and in particular much more sensitive to the local variation in household leverage, instrumented by exogenous variation in housing prices). Firms in tradable sectors such as manufacturing tend to be older and larger than in non-tradable sectors like the retail sector (although appropriate caution is required here in terms of distinguishing between establishment and firm size and age – note our focus is intentionally on firm size and firm age). Thus, it is possible that our results reflect differential responses across industries.

In this section, we estimate our panel VAR specification separately for each broad sector. For the sake of brevity, we focus on the responses of the net differential for young/small relative to the old/large firms in each sector. Moreover, we focus on the responses to the state-specific cyclical shocks and state-specific housing price shocks.[28]

The broad sectors we use are defined in a consistent manner from the 1981-2010 period. Specifically, the broad sectors are defined in a manner consistent with the SIC broad sectors by reallocating industries that switched broad sectors under NAICS back to their original SIC broad sectors. For example, this implies that we have switched Restaurants and Bars back into the Retail Trade sector during the NAICS (post-1997) period. We note that Mian and Sufi (2012) consider four broad sectors – Non-tradables, Tradables, Construction and Other industries. They define the Non-tradable sector as essentially the NAICS Retail Trade sector with Restaurants and Bars added back in (although they also consider a more narrow definition based on restaurants and grocery stores), the Tradable sector is mostly Manufacturing, the Construction sector is the building trades and the building materials components of Manufacturing, and their Other sector is everything else. Thus, our broad sectors provide a reasonable correspondence to their categories with our breaking out the other into the various broad sector components.

The impulse response functions for the net differential for young/small relative to old/large for each of the broad sectors are reported in Figures 9.a-Figure 9.g. We find that for all broad sectors, the state-specific cyclical shock decreases the net differential between young/small and old/large. That is, in all sectors, an increase in the unemployment rate in the state is associated with a decline in the net differential between young/small and old/large. We think it is noteworthy that even the Manufacturing sector ("Tradables") exhibits a large decline in the net differential of young/small relative to the old/large

[28] Analogous to the concerns expressed for the analysis of job creation and job destruction, one concern in comparing results across specifications that differ by sector is that the identified state cyclical shocks and housing price shocks and their respective dynamics vary across specifications. In practice, each of these sectoral specifications yields very similar state specific cyclical shocks and state specific housing price growth shocks.

with respect to a state-specific cyclical downturn. Apparently, young/small businesses are vulnerable to local downturns in all sectors.[29]

While our results on cyclical shocks are fairly robust within all sectors, the results on housing price shocks vary substantially by sector. In Construction, Retail Trade, FIRE and Services, we find that when housing prices decline the net differential between young/small businesses and old/large businesses declines. For Manufacturing, Wholesale Trade, and Transportation and Public Utilities, the estimated effects of housing price shocks on this same net differential are mostly small and insignificant, though for Manufacturing and Wholesale, they are negative rather than positive. That is, when housing prices decline we find that the net differential at impact widens in Manufacturing and Wholesale Trade.

Our finding that the net differential impact on young/small businesses holds within sectors such as Construction, Retail Trade, FIRE and Services indicates that our main results are not being driven by composition effects across industries. That is, our main results in section V.B, cannot be interpreted as suggesting that only some sectors are responsive to the local shocks and they happen to be sectors dominated by young/small businesses. Rather we find that in all sectors, young/small businesses are more sensitive to local shocks. We do find that the sensitivity to housing price shocks varies across sectors which is something we discuss in the next section.

E. Discussion

Our results highlight that young/small businesses respond more to state-specific cyclical and housing price shocks than do large/mature businesses. Both findings are of interest for understanding how firms of different size and age respond to business cycles. Moreover, we find that housing price shocks in some states and years (e.g., California in the 2007-09 period) account for a substantial fraction of the large reduction in the net differential between young/small and large/mature businesses over this period of time. These results point to the collapse of housing prices as being a major factor in the especially large decline of young/small businesses in the Great Recession.

We find that the large decline of young/small businesses in the Great Recession is associated with not only an especially large decline in job creation for such businesses, but also an especially large

[29] In unreported results, we have explored the net responses of all groups rather than the net differential responses to cyclical and housing price shocks. We find that all firm size/age groups in *all* sectors experience a decline in net employment growth in response to an increase in the state-specific unemployment rate. Consistent with our findings, we find that the magnitude of the response is largest for the young/small firms. The point is that the net differential responses are associated with all firm size and age groups experiencing a decline in local cyclical downturns but young/small experiencing the larger and that this pattern holds for all sectors. In response to housing price shocks, similar remarks apply but with the largest magnitude being for the young/small in the Construction, Retail Trade, FIRE and Service sectors.

increase in job destruction for such businesses. Moreover, we find that the greater responsiveness to state-specific cyclical shocks for young/small businesses holds within all of the broad sectors we consider. In contrast, the greater responsiveness to housing price shocks, are driven by greater responsiveness in the Construction, Retail Trade, FIRE and Services industries.

Our findings demonstrate that young/small businesses are more vulnerable to local cyclical shocks as well as to local housing price shocks. While we do not identify the specific mechanisms driving our results, the results themselves highlight the importance of these shocks on the more vulnerable populations for understanding the decline in economic activity in the Great Recession.

There are a number of mechanisms that may be underlying our results. It is beyond the scope of this paper to differentiate fully between them, but the remainder of this sub-section discusses possible alternatives. In considering possible mechanisms, it is important to remember the responses to both local (generic) cyclical shocks as well as to housing price shocks. Young/small businesses may be more sensitive to cyclical shocks due to differences in the nature of product and credit markets such businesses face. In terms of product markets, young/small businesses have not built up the customer base that large/older businesses have developed. Foster, Haltiwanger and Syverson (2012) show that even in the manufacturing sector for commodity goods like ready mix concrete, it takes significant time and investment in customer relationships by young businesses to grow and survive. In a related fashion, young/small businesses inherently have a customer base that is more local. In that respect, young/small businesses are more likely to be producing goods and services that are "non-tradables" in the sense of a limited geographic reach for such businesses (e.g., the small restaurant or store in the neighborhood).

Credit markets and financing frictions may also be an important mechanism behind our results. As we discussed in Section II, there are many theories and some evidence that young/small businesses are more likely to be credit constrained. A greater propensity to being credit constrained can lead to a greater sensitivity to local cyclical shocks. In addition, our results on housing price shocks suggest a specific mechanism for financing constraints. The literature described in Section II documents the reliance on home equity as a source of credit for startups and young businesses. The local decline in housing prices is associated with a large decline in home equity implying direct home equity financing is less available for startups and young businesses. Our findings that young/small businesses are more sensitive to the innovation in local housing prices abstracts from the endogenous component of local housing prices to the local cyclical shock. The results therefore provide strong evidence consistent with this financial constraint mechanism differentially affecting young/small firms.

While the home equity to financing channel is consistent with our results, we recognize that other channels could account for our findings. One alternative is the potential impact on consumption by households that is the focus of Mian and Sufi (2012). They find that areas with higher household leverage (which tend to be areas with greater run-up in housing prices), show bigger decreases in local consumption and also in employment in the tradable sectors. The Mian and Sufi mechanism therefore highlights the importance of housing prices on households' balance sheets, but points to its effect on local consumption rather than its role in facilitating financing options for young/small businesses.

Mian and Sufi's findings are relevant, but additional channels beyond the household balance sheet/consumption channel are necessary to account for our results on young/small differential responses to local cyclical shocks and local housing price shocks. First, we find that the greater response to young/small businesses to local cyclical shocks holds in all sectors – both tradable and non-tradable. In as much as the cyclical shock affects local consumption, then their local aggregate demand channel should be already captured at least in part by our local cyclical shock.[30] Second, we find that the greater response to young/small businesses to housing price shocks holds within non-tradable sectors. That is, some other mechanism other than the household balance sheet/consumption channel must be accounting for why young/small businesses within non-tradables are especially impacted. The Mian and Sufi mechanism also fails to explain all our results on the differential impact of housing prices. The result that the net differential effect of housing prices on young/small businesses is large in magnitude in the Construction and FIRE industries suggests that one part of the explanation may be the impact of housing prices on the local industries that are directly tied to housing – i.e., Construction and FIRE. But again, it is important to emphasize that our findings are not simply that these are industries hit hard when housing prices fall. A mechanism must also explain why it is the young/small businesses within these industries that are the most adversely affected.

While suggestive, these arguments do not necessarily imply that the home equity financing of young businesses is the mechanism at work. As we note above, the Mian and Sufi findings inherently point to the variation in housing prices as impacting the credit conditions faced by households. In that respect, we think that our findings should be interpreted as reflecting some form of credit channel. But as Mian and Sufi emphasize, a critical question is what households do with home equity, and more specifically, how households responded to their decreased home equity when housing prices collapsed. Identifying the use of home equity as a financing channel for young businesses will require more

[30] Pushing on this point further, our housing price shocks are orthogonal to the local cyclical shock. If the latter captures changes in local aggregate demand, then the variation in housing prices we exploit is orthogonal to local demand effects. We note that, in this regard, our results are robust to using a variety of indicators of local cyclical conditions including real GDP growth and real Personal Income growth.

evidence on the extent to which such financing varies by sector (since our results indicate the sensitivity to housing price shocks varies by sector) and the extent to which the usage of such financing changed when housing prices collapsed.

Concluding Remarks

In this paper we combine data from the Census Bureau's Business Dynamics Statistics (BDS) from 1981 to 2010 with indicators of business cycle and financial market conditions to examine the cyclical job dynamics of firms of different size and age. Specifically we exploit unique state and time variation in these data to identify the relative impact of business cycle and housing price shocks. We show that young and small businesses experienced especially large declines in net employment growth and job creation in the 2007-09 recession. We show that they also experienced large increases in job destruction over the same period. Large and mature businesses also experienced substantial declines in net employment growth over this period and since such firms account for most employment it follows that they account for a larger share of job loss. However, we find that young/small businesses are more cyclically sensitive so that the relative decline in this period is greater for young and small businesses than for large and mature businesses. Young and small businesses disproportionately contributed to the job loss over this period. Since young firms disproportionally contribute to job creation in any given year our results further indicate that the especially large decline of young and small businesses might be important for understanding not only the depth of the recession, but also the slow recovery after the official end of the recession. Research has shown that startups and young fast-growing U.S. businesses are important not only for U.S. jobs, but also for productivity growth. In as much as this recession has had a negative impact on a cohort of businesses that would otherwise have been born, the impact of the Great Recession has yet to be fully understood.

Why was the impact on young and small businesses especially large in this period? The evidence in this paper points to the collapse in housing prices playing a critical role. In states where housing prices declined the most (and after controlling for the endogenous impact of local business conditions on those prices), we find that there has been an especially large decline in the net employment growth for young and small businesses.

The mechanism(s) that accounts for the greater vulnerability of young and small businesses to cyclical shocks and housing price shocks is an open question. We think there are a number of channels possibly at work that make young and small businesses more vulnerable in general to cyclical shocks and to housing prices in particular. One possible channel of interest is a home equity financing of startups and young businesses. Research has shown that startups and young businesses use home equity for financing.

An open question is whether this is the mechanism that yielded the tight connection between the decline in housing prices and the decline in net growth for young and small businesses. Our findings also indicate that the impact of the collapse of housing prices on young and small businesses is concentrated in the Construction, Retail Trade, FIRE and Service sectors. As such, for the home equity financing channel of young businesses to be at work, we would need evidence that home equity financing of young businesses is especially important in these sectors. We think our findings suggest exploring this and alternative mechanisms should be an active area for future research but we recognize that this will likely require additional data to help us sort out the possible alternatives.

References

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error component models. *Journal of Econometrics*, *68*, 29–51.

Becker. Randy A., John Haltiwanger, Ron S. Jarmin, Shawn D. Klimek and Daniel J. Wilson, 2006, "Micro and Macro Data Integration: the Case of Capital", in A New Architecture for the U.S. National Accounts, (Jorgenson, Landefeld and Nordhaus eds), NBER/University of Chicago Press.

Bernanke, Ben and Mark Gertler (1989), "Agency Costs, Net Worth and Business Fluctuations," *The American Economic Review*, 79 (1), 14-31.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1999), "The Financial Accelerator in a Quantitative Business Cycle Framework," Handbook of Macroeconomics.

Chari, V.V., L. Christiano and P. Kehoe (2007), "The Gertler-Gilchrist Evidence on Small and Large Firm Sales," *mimeo*.

Davis, Stephen J., and John Haltiwanger (2001) "Sectoral Job Creation and Destruction Responses to Oil Price Changes and Other Shocks." *Journal of Monetary Economics*, December.

Davis, Stephen J., John Haltiwanger and Scott Schuh (1996), *Job Creation and Destruction*, MIT Press.

Davis, Stephen J., John Haltiwanger, Ron Jarmin and Javier Miranda, 2007. "Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms," NBER Chapters, in: NBER Macroeconomics Annual 2006, Volume 21, pages 107-180 National Bureau of Economic Research, Inc.

Decker, Ryan, John Haltiwanger, Ron Jarmin and Javier Miranda (2012), "The Secular Decline in Business Dynamism in the U.S.", mimeo.

Fazzari, Stephen, R. Glenn Hubbard, and Bruce Peterson (1988), "Financing Constraints and Corporate Investment," *Brookings Papers on Economic Activity*, 1, 141-95.

Foster, Lucia, John Haltiwanger, and Chad Syverson (2012), "The Slow Growth of New Plants: Learning about Demand," NBER Working Paper No. 17853.

Gertler, Mark and R. Glenn Hubbard, "Financial Factors in Business Fluctuations," in Financial *Market Volatility: Causes, Consequences, and Policy* (Kansas City: Federal Reserve Bank of Kansas City), 33-71.

Gertler, Mark and Simon Gilchrest (1994), "Monetary Policy, Business Cycles, and the Behavior of Small Manufacturing Firms," *The Quarterly Journal of Economics*, 109 (2), 309-340.

Gilchrist, Simon and Vladimir Yankov and Egon Zakrajsek (2009), "Credit Market Shocks and Economic Fluctuations: Evidence from Corporate Bond and Stock Markets," *NBER*, Working Paper: 14863, April 2009.

Haltiwanger, John (2010), "The Changing Cyclical Dynamics of U.S. Labor Markets," mimeo.

Haltiwanger, John, Ron Jarmin and Javier Miranda (2009), "Business Dynamic Statistics: An Overview" Marion Ewing Kauffman Foundation BDS Briefs.

Haltiwanger, John and Ron Jarmin and Javier Miranda (2010), "Who Creates Jobs? Small vs. Large vs. Young," *NBER*, Working Paper: 16300, August 2010 (forthcoming in the *Review of Economics and Statistics*).

Holtz-Eakin, Douglas, Whitney Newey and Harvey S. Rosen (1988), "Estimating Vector Autoregressions with Panel Data," *Econometrica*, Vol. 56, No. 6, pp. 1371-1395.

Jarmin, Ron S., and Javier Miranda (2002), "The Longitudinal Business Database," CES Working Paper 02-17.

Krainer, John (2004), "What Determines the Credit Spread?," *FRBSF Economic Letter*, 36.

Love, Inessa and Lea Zicchino (2006), "Financial development and dynamic investment behavior: Evidence from panel VAR", The Quarterly Review of Economics and Finance, 46 (2006) 190–210.

Mach, Traci and John Wolken (2006), "Evidence from the 2003 Survey of Small Business Finances," *Federal Reserve Bulletin*, 92, A167-A195.

Mian, Atif and Amir Sufi (2010), "Household Leverage and the Recession of 2007-09", IMF Economic Review, (58) 74-116.

Mian, Atif and Amir Sufi (2011), "House Prices, Home Equity-Based Borrowing, and the U.S. Household Leverage Crisis", *American Economic Review*, 101, 2132-2156.

Mian, Atif and Amir Sufi (2012), "What Explains High Unemployment? The Aggregate Demand Channel" mimeo.

Mishkin, Frederic S. (2008), "Small Business Lending," Testimony before the Committee on Small Business and Entrepreneurship, U.S. Senate, April 2008.

Moscarini, Guiseppe and Fabien Postel-Vinay (2008), "The Timing of Labor Market Expansions: New Facts and a New Hypothesis," in D. Acemoglu, K Rogoff, and M. Woodford., eds, *NBER Macroeconomics Annual*, 23, 1-51.

Moscarini, Guiseppe and Fabien Postel-Vinay (2012), "The Contribution of Large and Small Employers to Job Creation in Times of High and Low Unemployment", *American Economic Review*.

Mueller, Philippe (2009), "Credit Spreads and Real Activity," *mimeo*.

Robb, Alicia and David Robinson, "The Capital Structure Decisions of Startup Firms," *Review of Financial Studies*, forthcoming.

Robb, Alicia and John Wolken (2002), "Firm, Owner, and Financing Characteristics: Differences between Female– and Male-owned Small Businesses," *Federal Reserve Board Finance and Economics Discussion Series Paper*.

Saiz, Albert Saiz (2011) "The Geographic Determinants of Housing Supply," *Quarterly Journal of Economics*, forthcoming.

Sharpe, Stephen (1994) “Financial Market Imperfections, Firm Leverage, and the Cyclicality of Employment,” *American Economic Review*, 84(4), 1060-74.

Stock, James H. and Mark W. Watson (2003) “Forecasting Output and Inflation: The Role of Asset Prices,” *Journal of Economic Literature*, 41(3), 788-829.

Tornqvist, Leo, Pentti Vartia and Yrjo Vartia (1985), “How Should Relative Changes Be Measured?” *American Statistician*, February, 39:1, pp. 43-46.

Measurement and Data Appendix

A1: Measurement of Net and Gross Job Flows

Our measures are taken from the Business Dynamic Statistics. The net job creation and gross job flow measures are based on the methodology of Davis, Haltiwanger and Schuh (1996). In the BDS, establishments are classified by their parent firm's size and firm age. This is based on the parent firm for the establishment. Firm size is available using both current average size (the average size of the parent firm in the prior and current year) and initial size (the size of the parent firm in the prior year). Firm age is based on the age of the oldest establishment when a new firm is started and then ages naturally thereafter. It is based on the parent firm in the current year. As noted in the text we collapse the available firm size and firm age categories into broad firm size and firm age categories. For any given cell "s" defined by a firm size and firm age category is equal to:

$$g_{st} = \frac{E_{st} - E_{st-1}}{X_{st}}$$

where $E_{st}$is employment for cell "s" in period t, $X_{st} = 0.5 * (E_{st} + E_{st-1})$.[31] In measuring and defining E_{st-1} it is critical to emphasize that this is the employment in period t-1 of the establishments that are in cell "s" in period t. That is, this is based on the same set of establishments in period t-1 and t (and this is not subject to the "size distribution fallacy" discussed in Davis, Haltiwanger and Schuh (1996) wherein misleading inferences can be generated by considering cell based totals of establishments classified by firm size (or firm age) across years as establishments can change firm size and firm age classifications). Another way of making this point is to note that that the growth rate for the cell can be equivalently generated by:

$$g_{st} = \sum_{e \in s} \frac{X_{est}}{X_{st}} \left(\frac{E_{est} - E_{est-1}}{X_{est}} \right) = \sum_{e \in s} \frac{X_{est}}{X_{st}} g_{est}$$

The net growth rate for the cell can be decomposed into the contribution of job creation and destruction as follows. Define job creation and job destruction for the cell as:

$$JC_{st} = \sum_{e \in s} \frac{X_{est}}{X_{st}} \max(g_{est}, 0)$$

$$JD_{st} = \sum_{e \in s} \frac{X_{est}}{X_{st}} \max(-g_{est}, 0)$$

By construction, net employment growth for the cell can be decomposed into:

$$g_{st} = JC_{st} - JD_{st}$$

[31] This measure of net growth is bounded between (-2,2) and is symmetric around zero. Its desirable properties are discussed extensively in Davis, Haltiwanger, and Schuh (1996).

Note that the cells for young firms include establishments of new firms (firm age=0). All such establishments have DHS net growth rates at the establishment level equal to 2. For the young firm cell, when there is a decrease in the share of young firm employment accounted for by new firms, the cell based growth rate will decline. But the net growth rate for the young firm cells will also reflect the job creation of firms older than firm age=0 as well as the job destruction of firms older than firm age=0.

A2: Cyclical variable construction

Unemployment rate: The national unemployment rate is based on quarterly data from the Bureau of Labor Statistic's (BLS) Current Population Survey for 1979-2010 . The state-level unemployment data are also quarterly and come from the BLS regional and state-level data releases available on FRED. We construct yearly data for the regression analysis by averaging the unadjusted, quarterly data over the re-timed year. We calculate the yearly change as: $\delta U_t = U_t - U_{t-1}$, where t represents the re-timed year. We also HP filter the unemployment as an alternative measure that captures deviations from the long-term trend.

Real GDP and Real Personal Income: Quarterly Real GDP at the national level is readily available from the BEA (Real GDP is nominal GDP deflated by the GDP implicit price deflator). We take time averages for the retimed year and compute log first differences. At the state level, nominal GDP is available on an annual basis but not for the re-timed year. Since the re-timed year is only off by a quarter we use this in our analysis with appropriate caution. We deflate the state level nominal GDP with the national implicit price deflator and then compute growth rates with log first differences. At the state level, a related alternative measure is available quarterly – personal income. The latter is income from all sources available to households. We deflate the latter on a quarterly basis with the national implicit price deflator, take averages for the re-timed year and then compute growth rates with log first differences.

Corporate spread: The corporate spread variable is based on monthly data of the difference between Moody's AAA Corporate Yield and the Merrill Lynch High Yield Red 100. We construct quarterly data by averaging the monthly data over year. To construct the yearly data for the regression analysis, we average the quarterly data over the re-timed year. We then HP filter the data to calculate yearly deviations from the long-term trend.

Housing Prices: The housing price measure is based on the Federal Housing Finance Agency (FHFA) House Price Index. The HPI is a weighted, repeat-sales index. It measures the average price changes in repeat sales or refinancings on the same properties. The information for the HPI is obtained from repeat mortgage transactions on single-family properties whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac since January 1975.

We use unadjusted HPI data that are quarterly, by state. We divide the HPI by the BLS Urban Consumer Price Index for all items so that the data are in real terms. We then average the quarterly index over the re-timed year and calculate the log first difference in home prices.

Table 1 Descriptive Regressions at National Level

	(1)	(2)	(3)	(4)	(5)	(6)
	net_rate_All	net_rate_11	net_rate_21	net_rate_12	net_rate_22	net_rate_32
Chg UR	-1.178***	-1.386**	-0.909	-0.448	-1.133***	-1.127***
	(0.214)	(0.487)	(0.511)	(0.317)	(0.292)	(0.216)
Int_Rt_Sprd	-0.653**	-0.612	-1.357*	-0.420	-0.791*	-0.583*
	(0.218)	(0.496)	(0.520)	(0.322)	(0.297)	(0.220)
GR_HPrice	0.045	0.520**	0.383*	0.165	0.066	-0.020
	(0.064)	(0.145)	(0.152)	(0.094)	(0.087)	(0.064)
N	30	30	30	30	30	30

The dependent variable is the net employment growth rate for the group specified. Chg UR is the unemployment growth rate; Int_Rt_Sprd is the HP filtered spread between Moody's AAA and the ML High Yield; GR_HPrice is the growth rate of the real FHFA housing price index. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium, 32=Old/Large

Table 2 Correlations Between Cyclical Indicators and Net Differential Employment Growth Rates

	Change in Unemp Rate		Net Emp. Growth Rate		Real GDP Growth		HP Filtered Unemp Rate	
	1981-2010	1981-2006	1981-2010	1981-2006	1981-2010	1981-2006	1981-2010	1981-2006
Young/Small-Older/Large	-0.452	-0.292	0.551	0.279	0.527	0.305	0.239	0.215
	(0.012)	(0.148)	(0.002)	(0.168)	(0.003)	(0.130)	(0.203)	(0.292)
Young/Medium-Older/Large	-0.342	-0.263	0.507	0.329	0.475	0.344	0.125	-0.057
	(0.064)	(0.194)	(0.004)	(0.101)	(0.008)	(0.085)	(0.512)	(0.782)
Older/Small-Older/Large	0.283	0.342	0.146	-0.258	-0.171	-0.242	0.608	0.620
	(0.130)	(0.087)	(0.441)	(0.204)	(0.367)	(0.233)	(0.000)	(0.001)
Older/Medium-Older/Large	-0.218	-0.075	0.403	0.267	0.313	0.162	0.391	0.551
	(0.247)	(0.715)	(0.027)	(0.188)	(0.092)	(0.429)	(0.033)	(0.004)

Note: P-values in parentheses.

Table 3 Descriptive Regressions at State Level (Controlling for State and Year Fixed Effects) – Using State-Level Change in Unemployment Rate as Cyclical Indicator

Bivariate

	(1)	(2)	(3)	(4)
	diff_net_rate_11	diff_net_rate_21	diff_net_rate_12	diff_net_rate_22
Chg_UR_st	-2.207***	-1.432***	-0.570***	-0.479***
	(0.212)	(0.248)	(0.142)	(0.140)

Multivariate

	(1)	(2)	(3)	(4)	
	diff_net_rate_11	diff_net_rate_21	diff_net_rate_12	diff_net_rate_22	
Chg_UR_st	-1.916***	-1.347***	-0.484***	-0.437**	
	(0.213)	(0.253)	(0.144)	(0.143)	
GR_HPrice_st	0.183***	0.054	0.054**	0.026	
	(0.027)	(0.032)	(0.018)	(0.018)	
N	1530	1530	1530	1530	
N	30	30	30	30	30

The dependent variable is the differential net employment growth rate for the group specified. All net differentials are with respect to Old/Large. Ch_UR_st is the state unemployment growth rate; GR_HPrice_st is the growth rate of the state's real FHFA housing price index. Standard errors in parentheses.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.00$. Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium.

Table 4 Descriptive Regressions at State Level (Controlling for State and Year Fixed Effects) – Using HP Filtered State-Level Unemployment Rate as Cyclical Indicator

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
HP_UR_st	-2.406***	-0.914*	-0.885***	-0.456*
	(0.347)	(0.401)	(0.227)	(0.225)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
HP_UR_st	-1.731***	-0.657	-0.708**	-0.353
	(0.355)	(0.417)	(0.236)	(0.234)
GR_HPrice_st	0.195***	0.074*	0.051**	0.030
	(0.028)	(0.033)	(0.019)	(0.019)
N	1530	1530	1530	1530

The dependent variable is the differential net employment growth rate for the group specified. All net differentials are with respect to Old/Large. HP_UR_st is the HP-filtered state unemployment rate; GR_HPrice_st is the growth rate of the state's real FHFA housing price index. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium.

Table 5 Descriptive Regressions at State Level (Controlling for State and Year Fixed Effects) – Using State-Level Change in Unemployment Rate as Cyclical Indicator, Post-2006 data excluded

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
Chg_UR_st	-2.145***	-1.389***	-0.405*	-0.384*
	(0.241)	(0.275)	(0.161)	(0.157)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
Chg_UR_st	-1.928***	-1.330***	-0.356*	-0.370*
	(0.240)	(0.278)	(0.162)	(0.159)
GR_HPrice_st	0.196***	0.054	0.044*	0.013
	(0.031)	(0.036)	(0.021)	(0.020)
N	1326	1326	1326	1326

The dependent variable is the differential net employment growth rate for the group specified. All net differentials are with respect to Old/Large. Ch_UR_st is the state unemployment growth rate; GR_HPrice_st is the growth rate of the state's real FHFA housing price index. Standard errors in parentheses.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium.

Figure 1

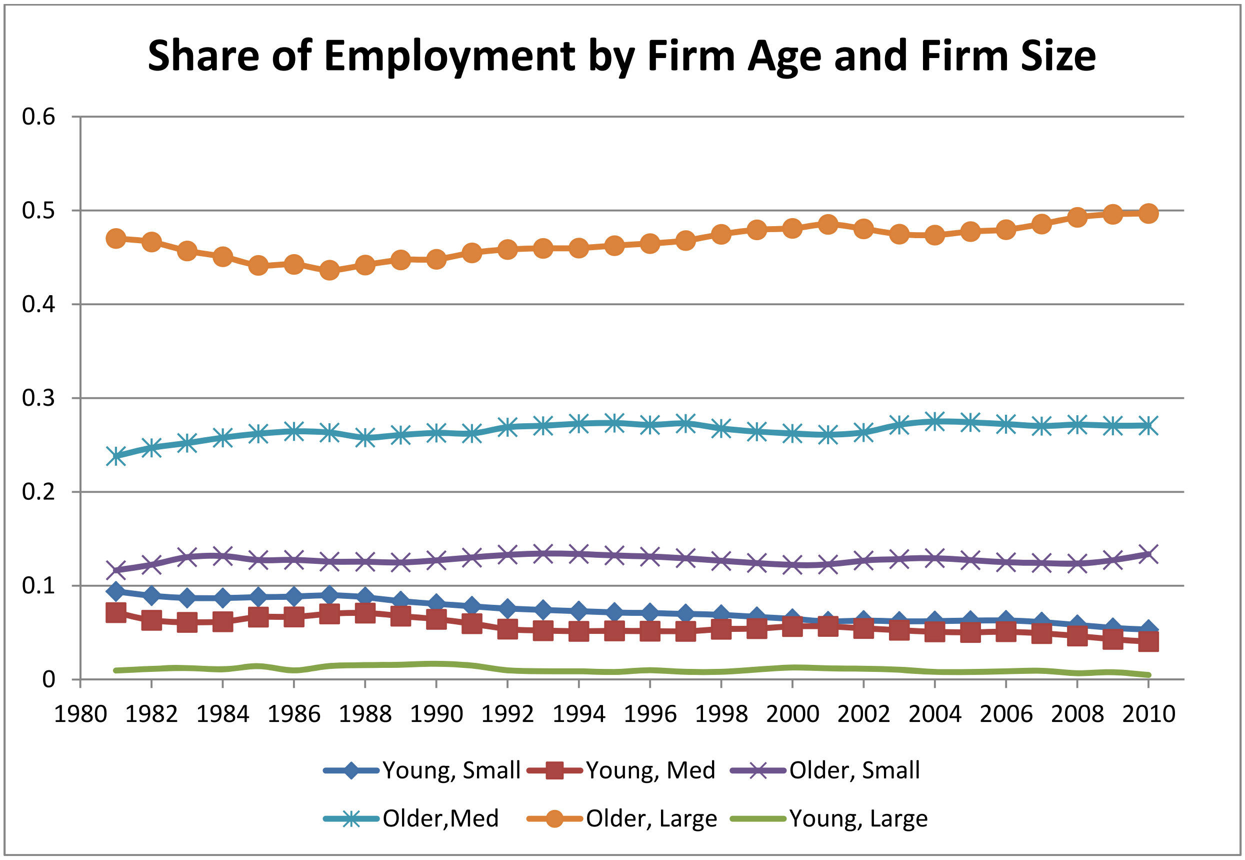

Share of Employment by Firm Age and Firm Size
0.6
0.5
0.4
0.3
0.2
0.1
0
1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010
Young, Small
Young, Med
Older, Small
Older,Med
Older, Large
Young, Large

Figure 2

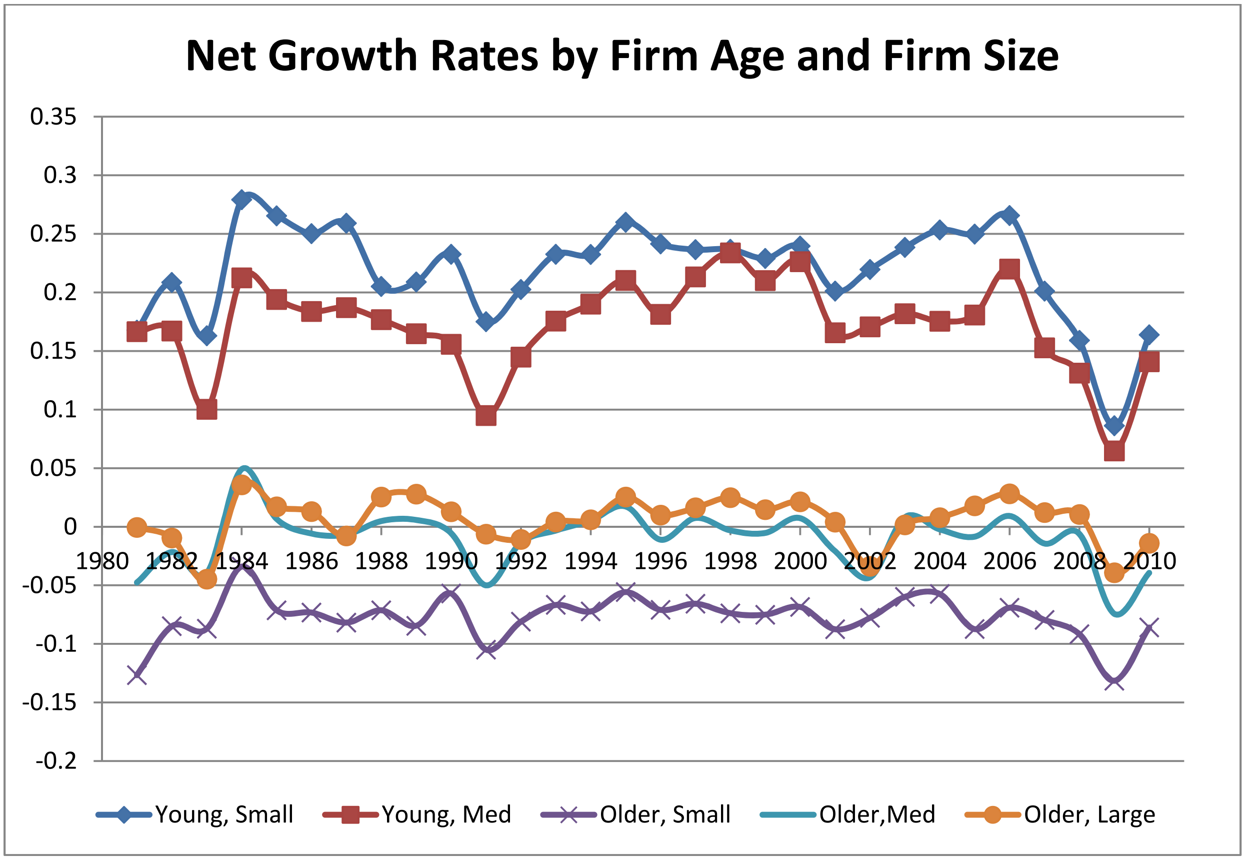
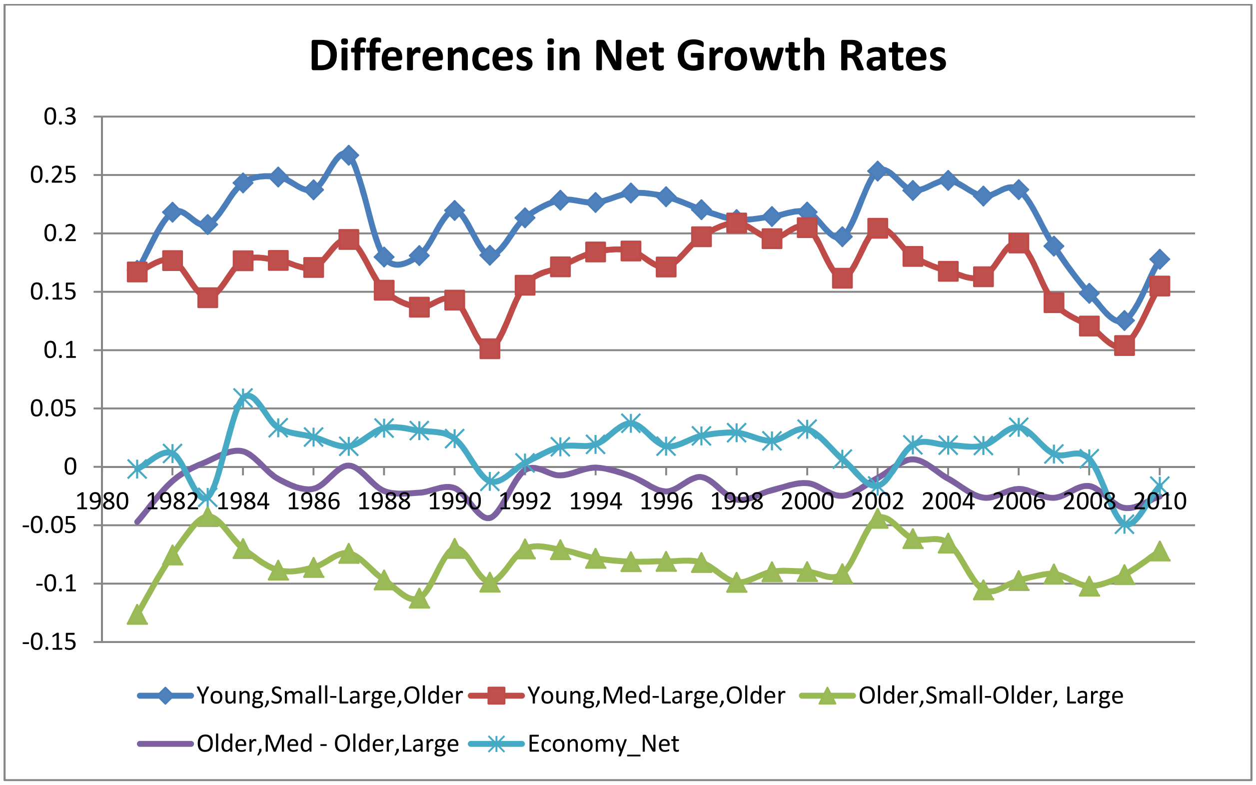

Net Growth Rates by Firm Age and Firm Size
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
1980 1982 1984 1986 1988 1990 1992 1994 1996 1998 2000 2002 2004 2006 2008 2010
Young, Small
Young, Med
Older, Small
Older,Med
Older, Large

Figure 3



Differences in Net Growth Rates
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
Young,Small-Large,Older
Young,Med-Large,Older
Older,Small-Older, Large
Older,Med - Older,Large
Economy_Net

Figure 4.a

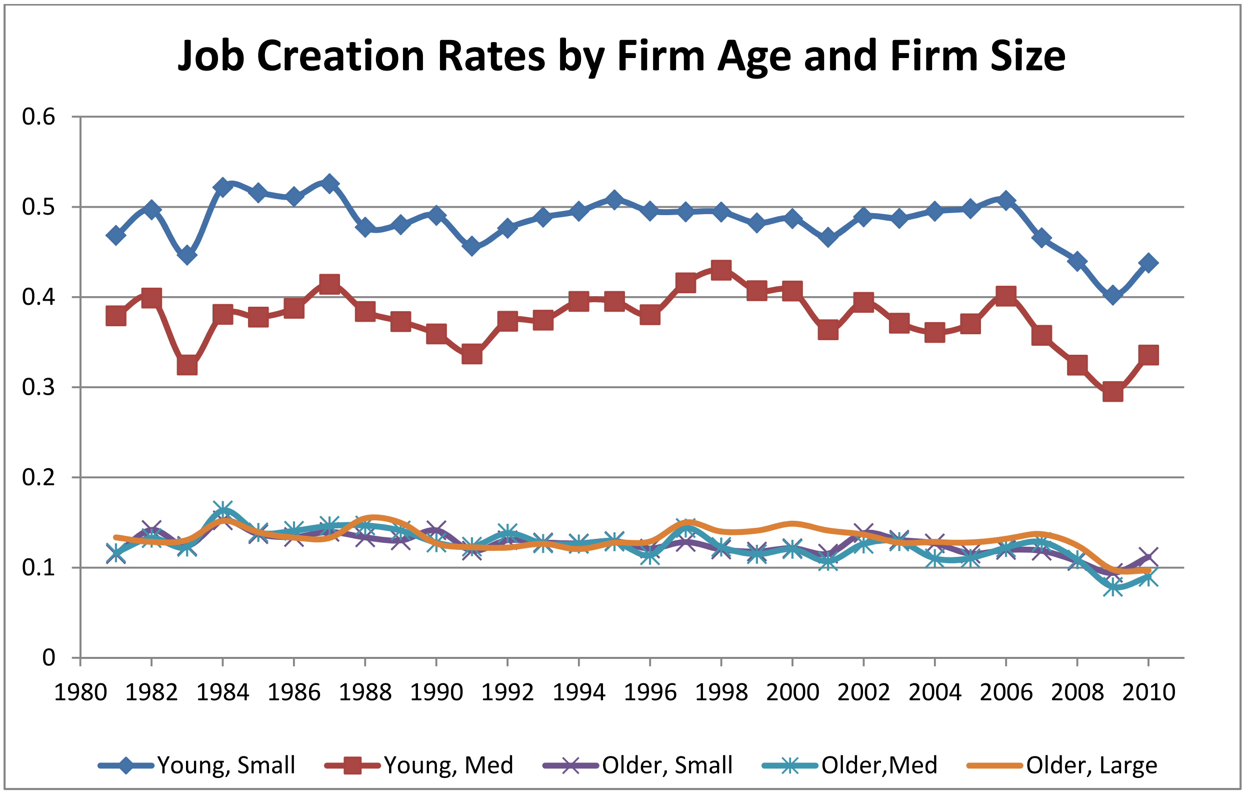


Figure 4.b

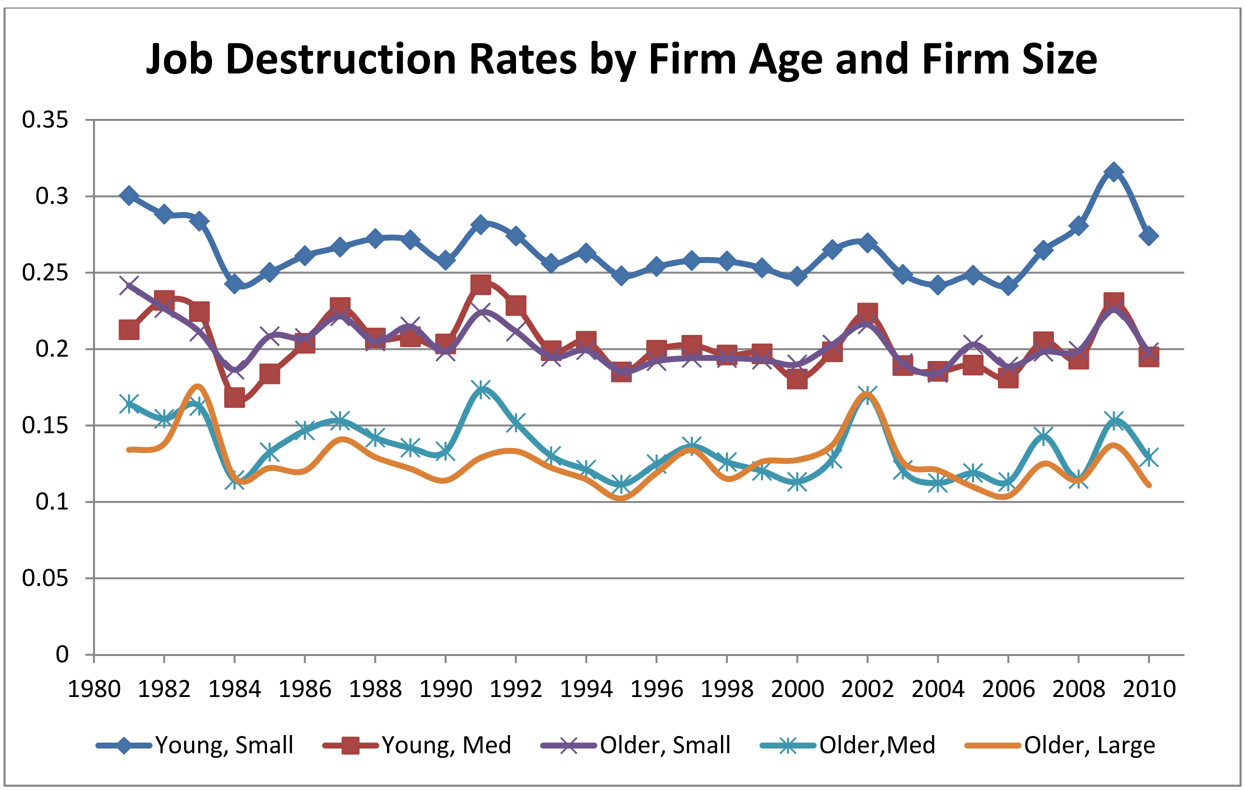


Figure 5.1

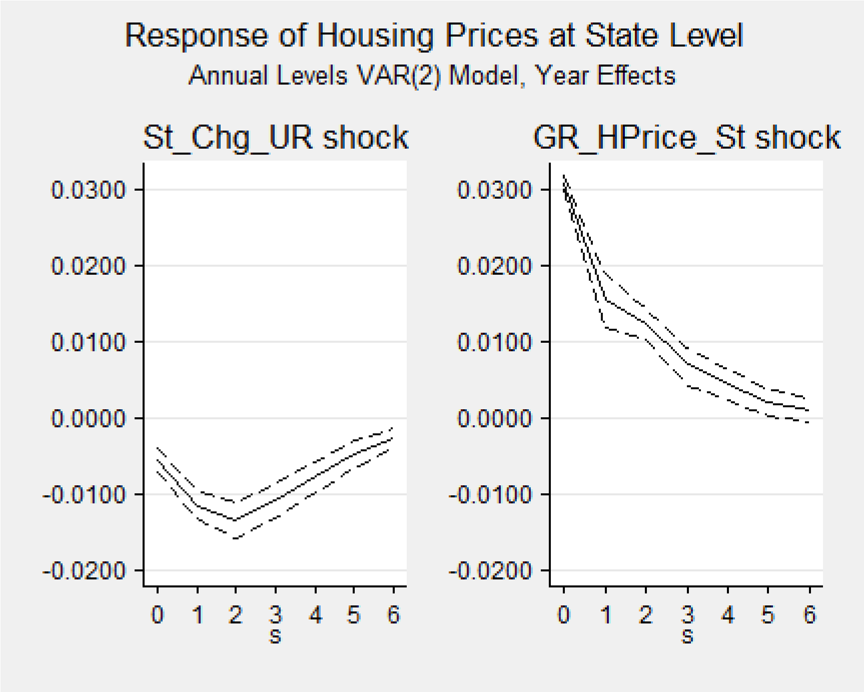


Figure 5.2

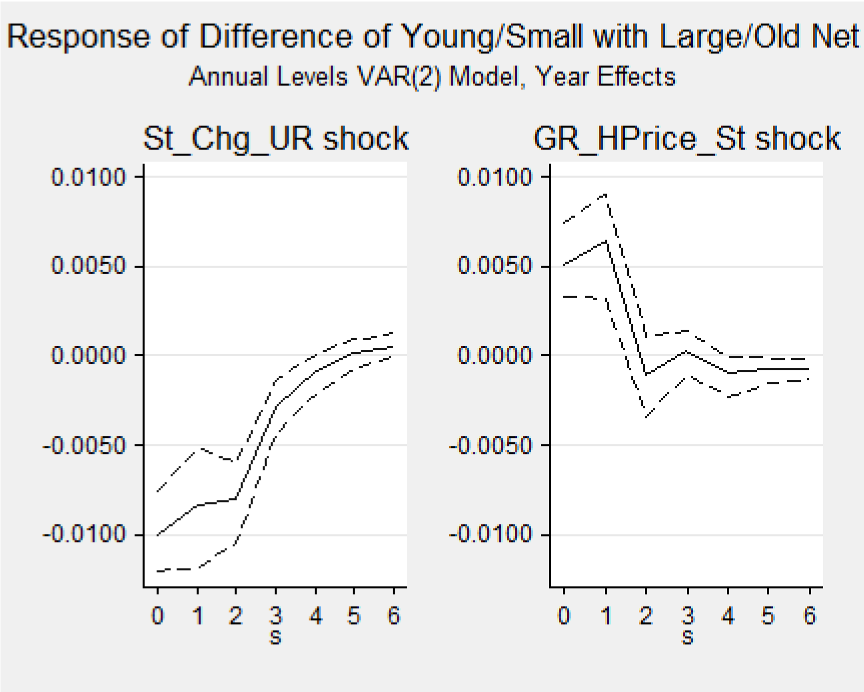


Figure 5.3

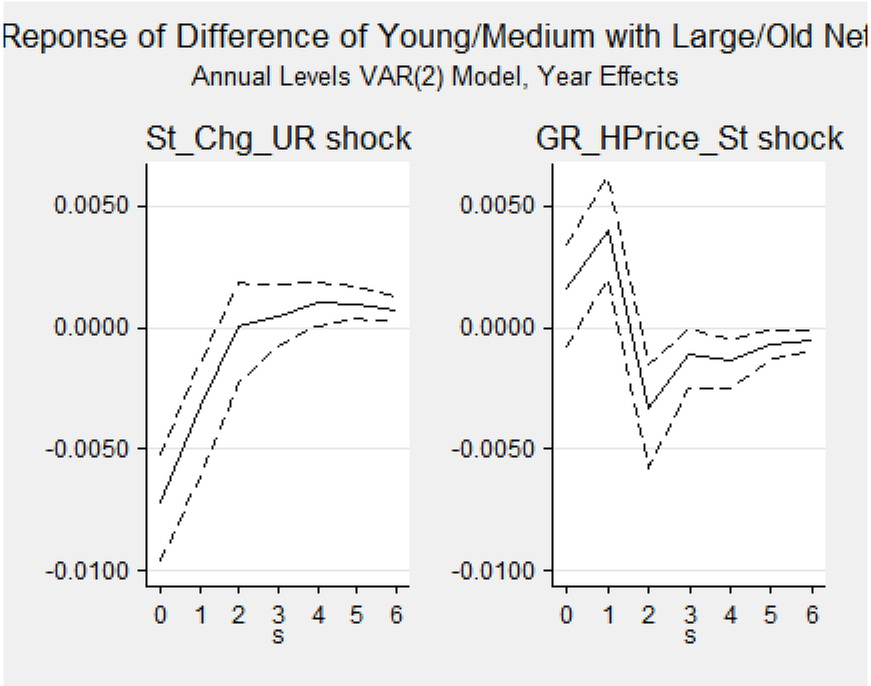


Figure 5.4

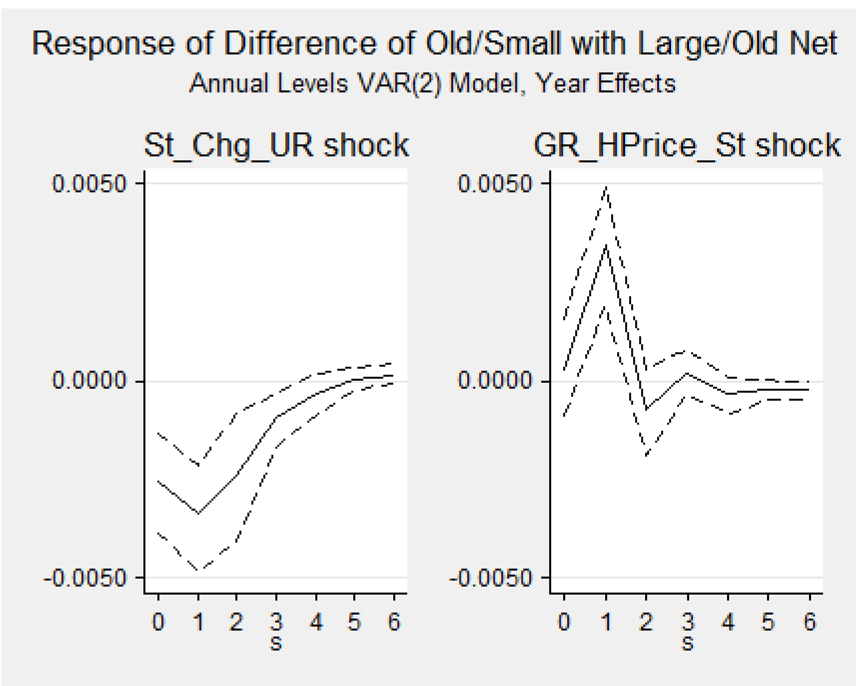


Figure 5.5

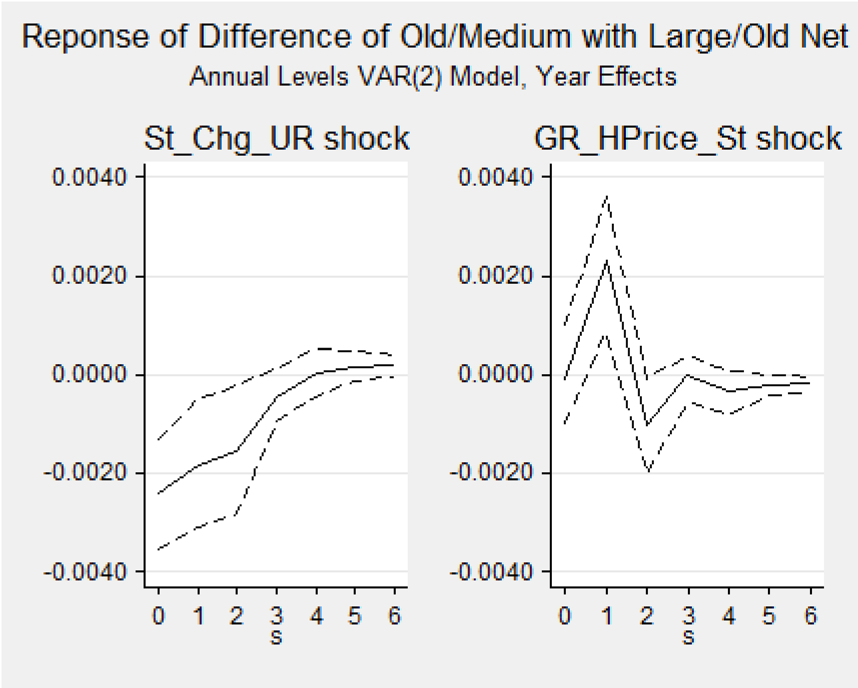

Reponse of Difference of Old/Medium with Large/Old Net
Annual Levels VAR(2) Model, Year Effects
St_Chg_UR shock
GR_HPrice_St shock
0.0040
0.0020
0.0000
-0.0020
-0.0040
0 1 2 3 4 5 6
s

Figure 6

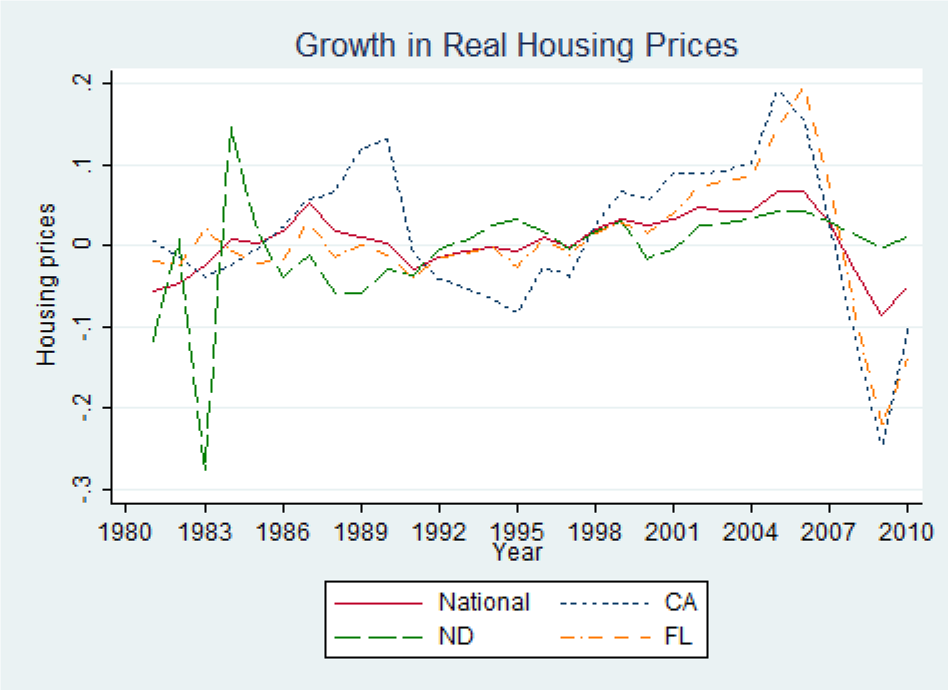


Figure 7

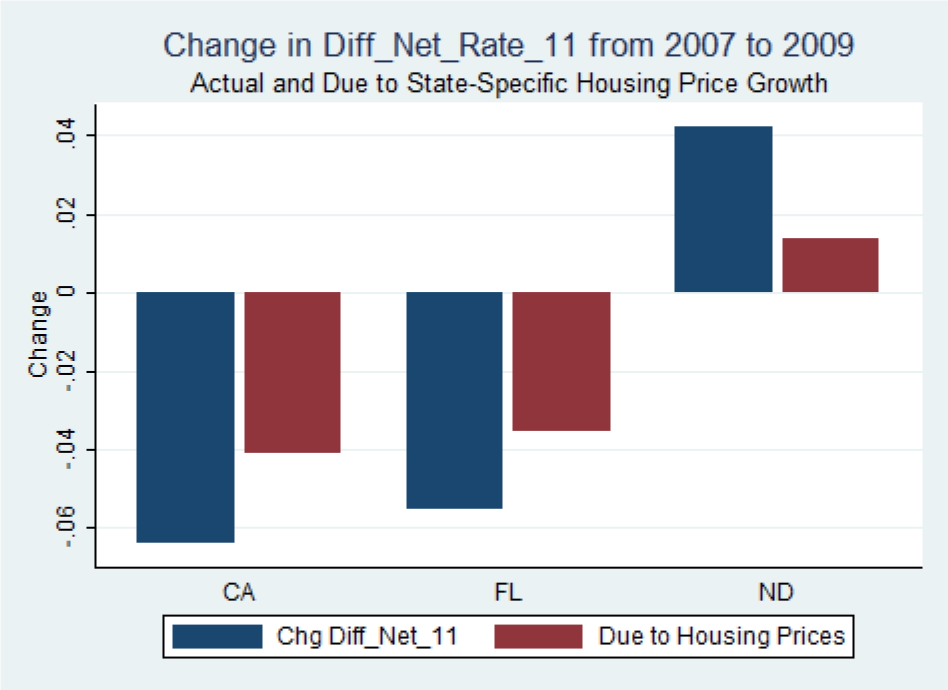


Figure 8.a Job Creation Differential Response

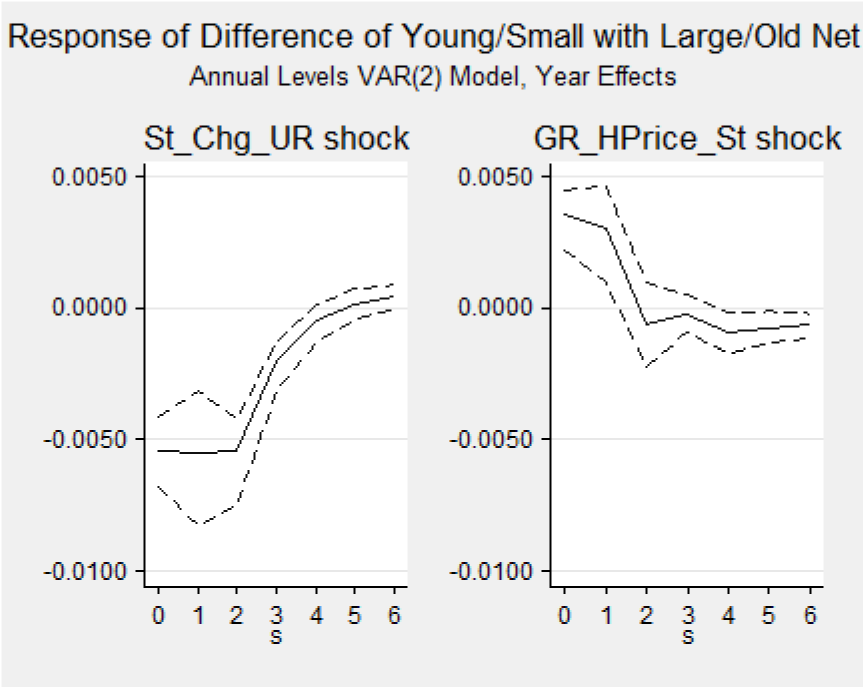


Figure 8.b Job Destruction Differential Response

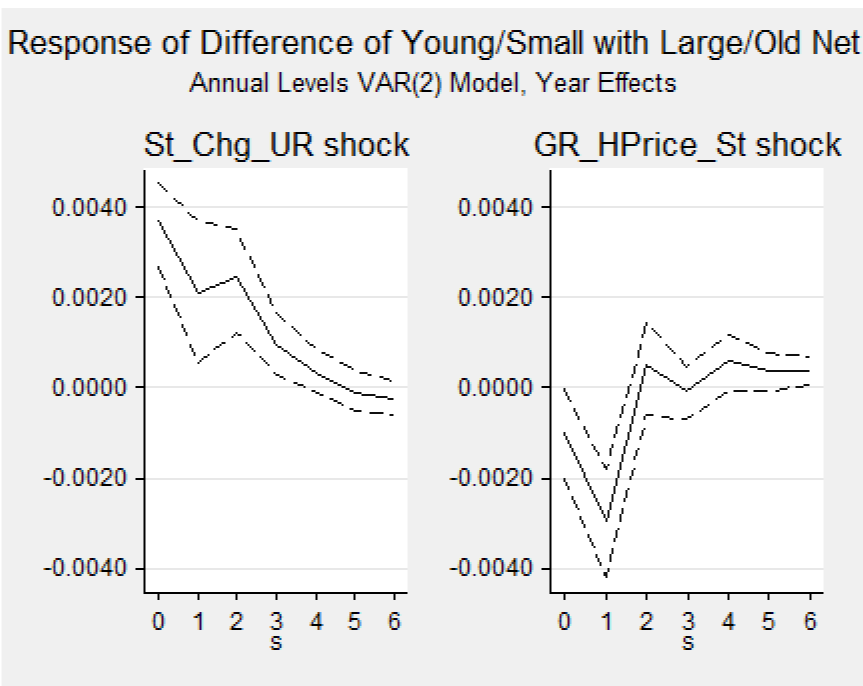


Figure 9.a. Net Differential Response for Construction

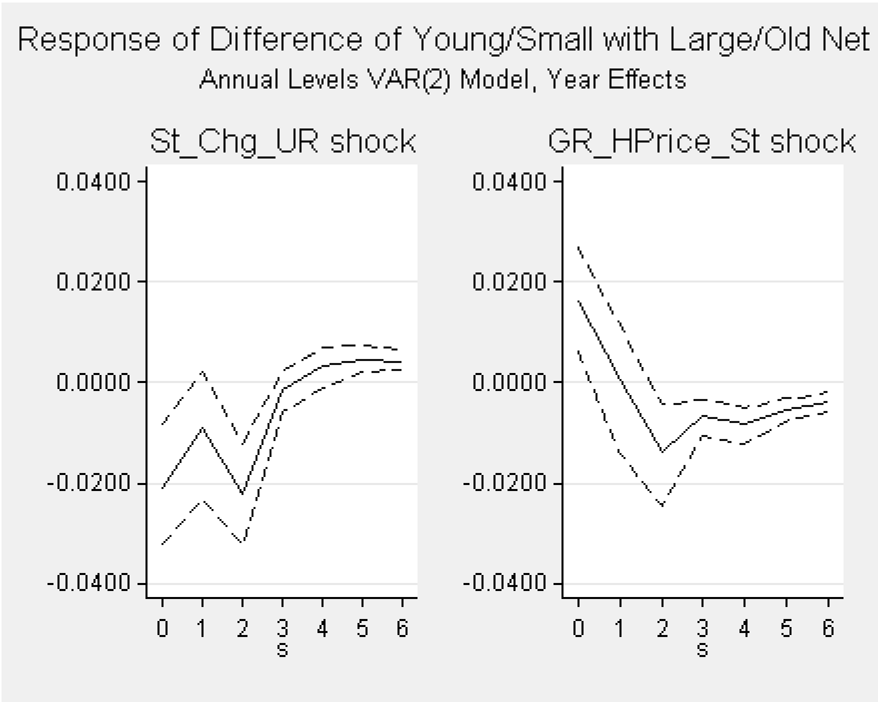


Figure 9.b Net Differential Response for Manufacturing

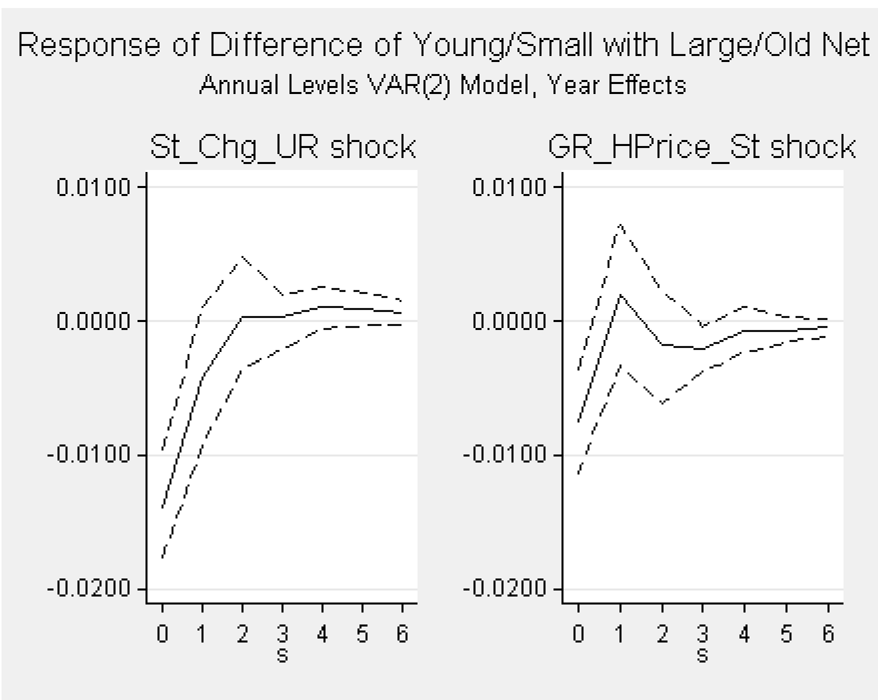


Figure 9.c Net Differential Response for Retail Trade

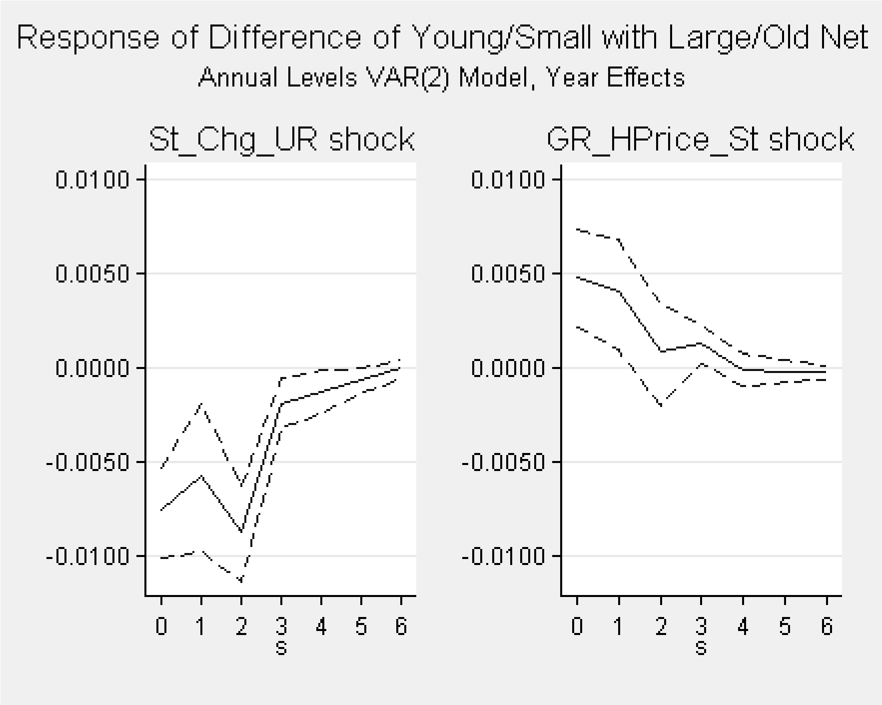


Figure 9.d Net Differential Response for Wholesale Trade

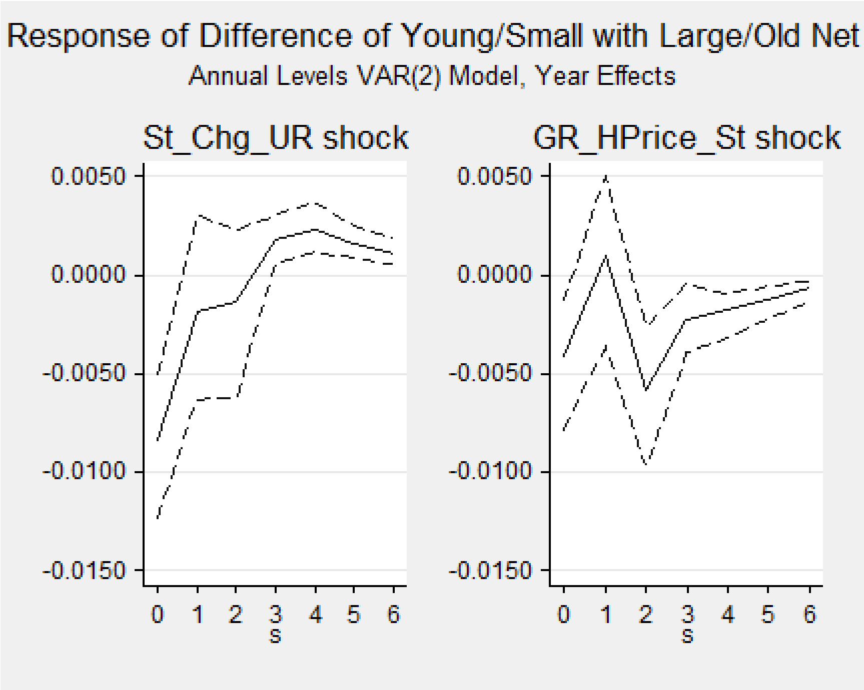


Figure 9.e Net Differential Response for FIRE

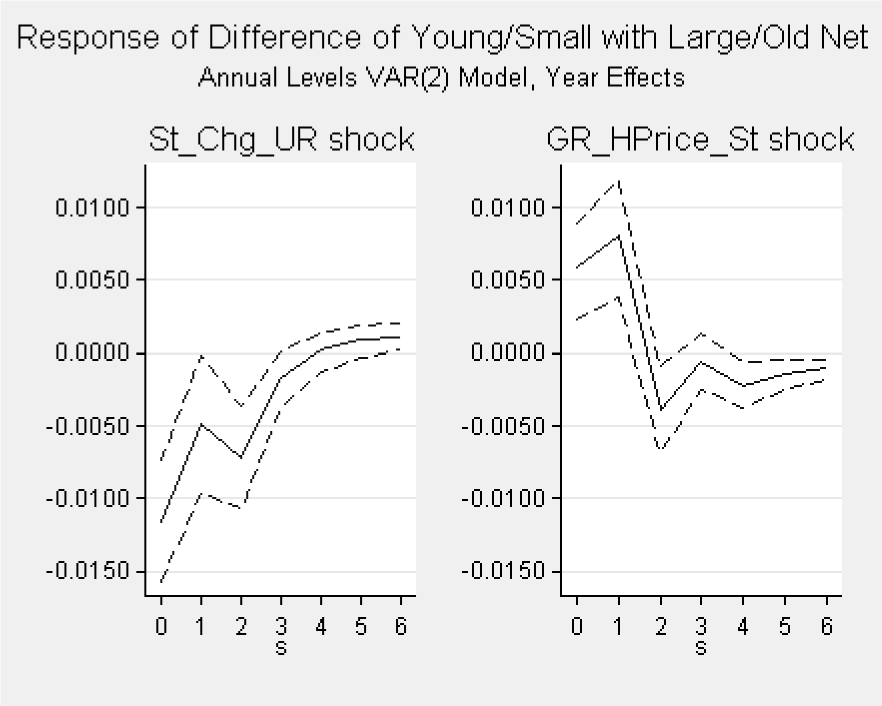


Figure 9.f Net Differentials for Services

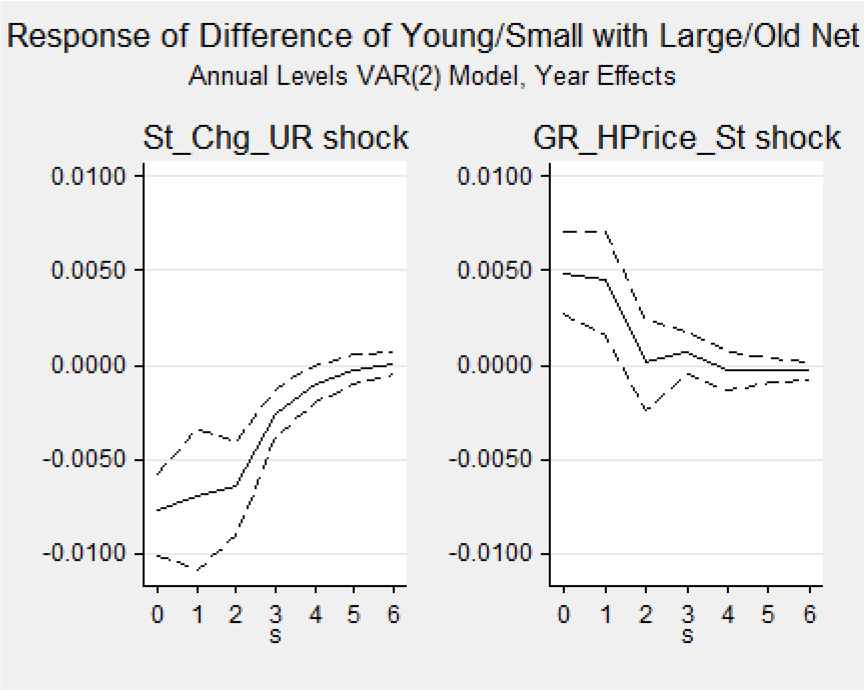
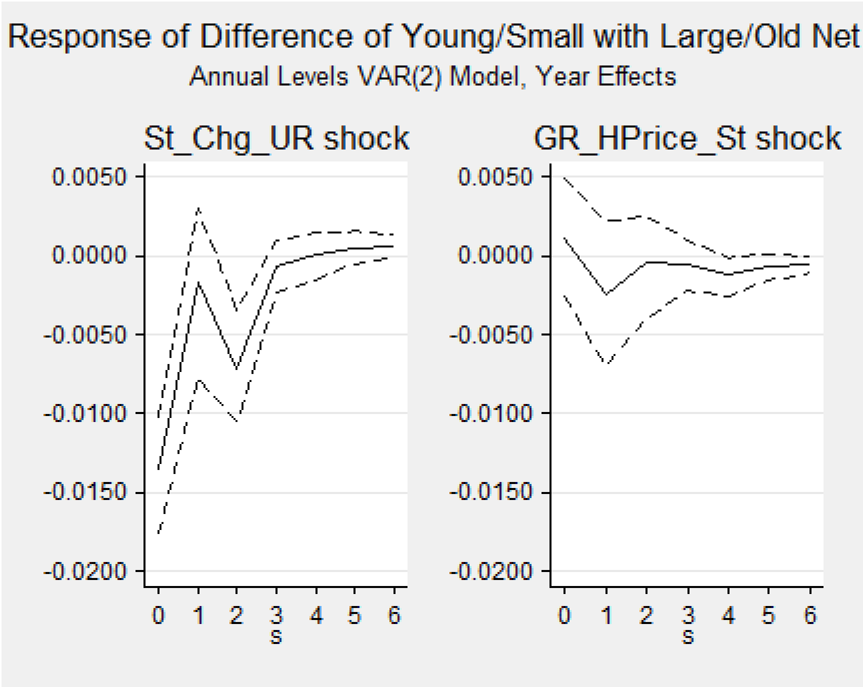


Figure 9.g Net Differential Response for Transportation and Public Utilities



Appendix Tables and Figures

Figure A.1.1 Using State Net Employment Growth as Cyclical Indicator

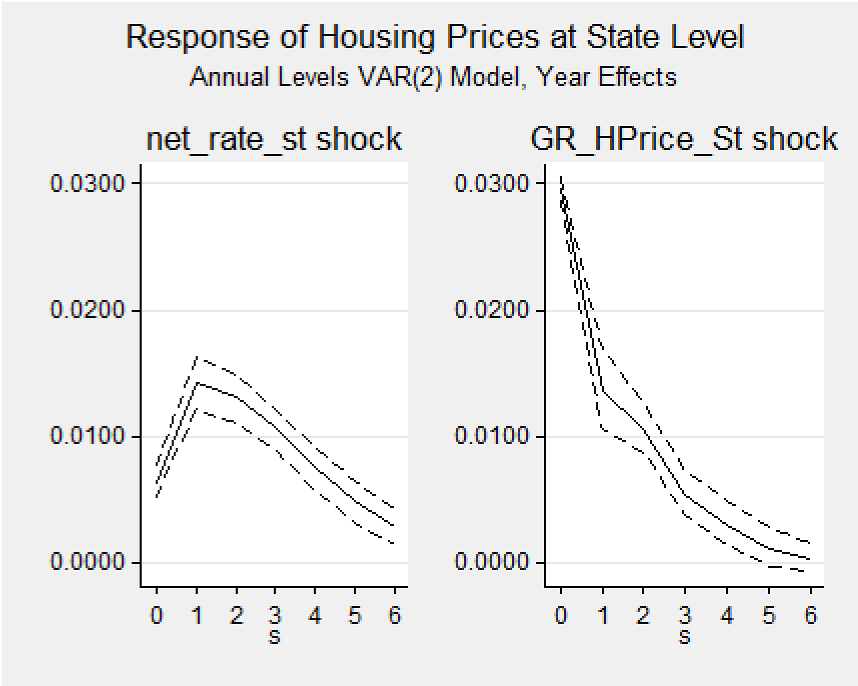


Figure A.1.2 Using Net Employment Growth Rate for Cyclical Shock

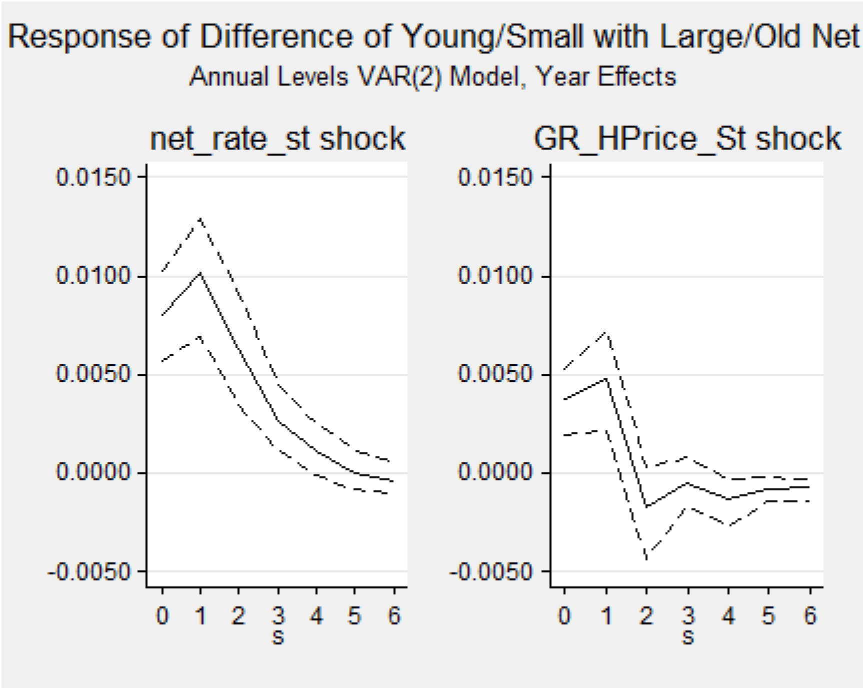


Figure A.1.3 Using Net Employment Growth Rate for Cyclical Shock

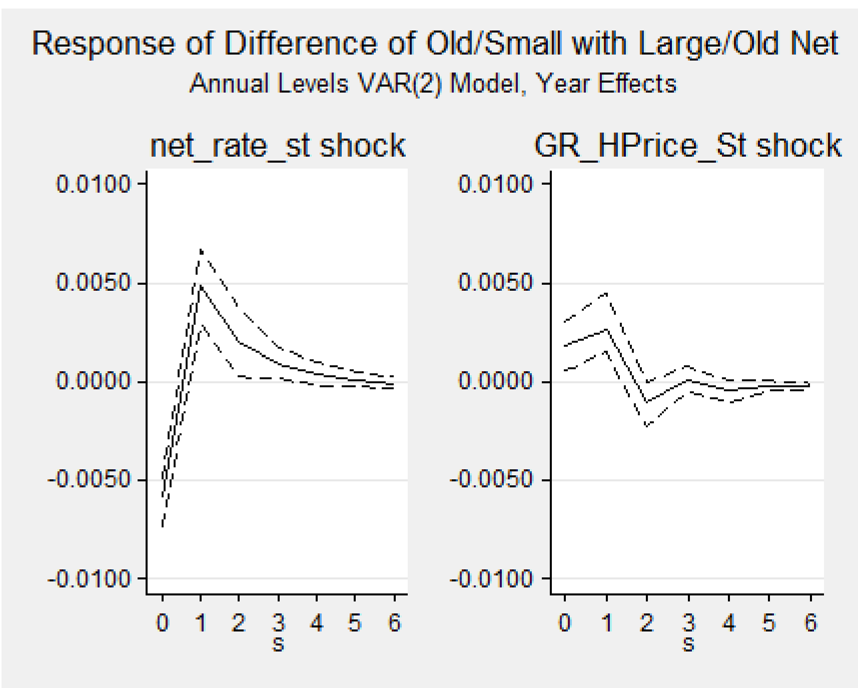


Figure A.1.4 Using HP-filtered State Unemployment Rate

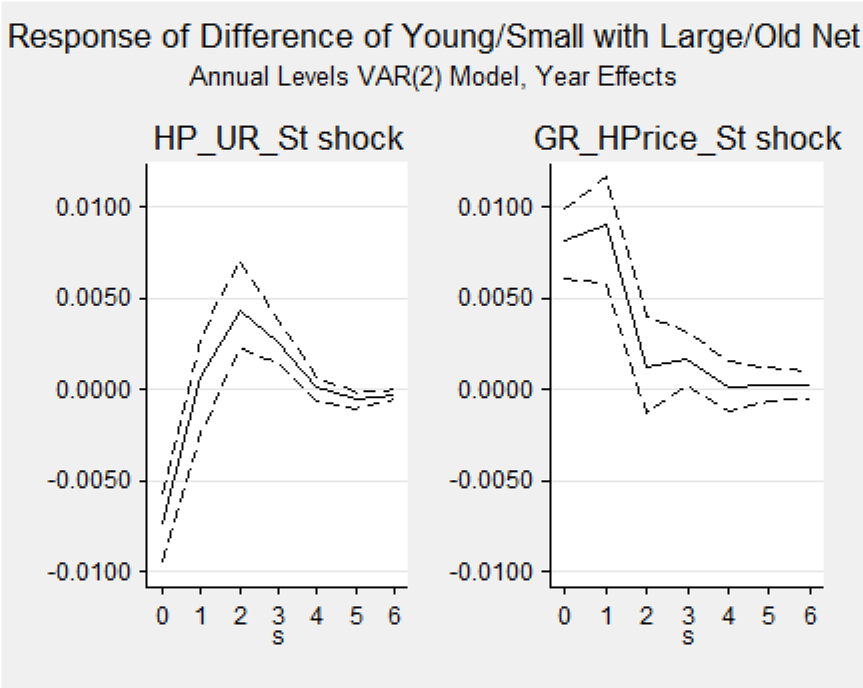


Figure A.1.5 Using HP-filtered State Unemployment Rate

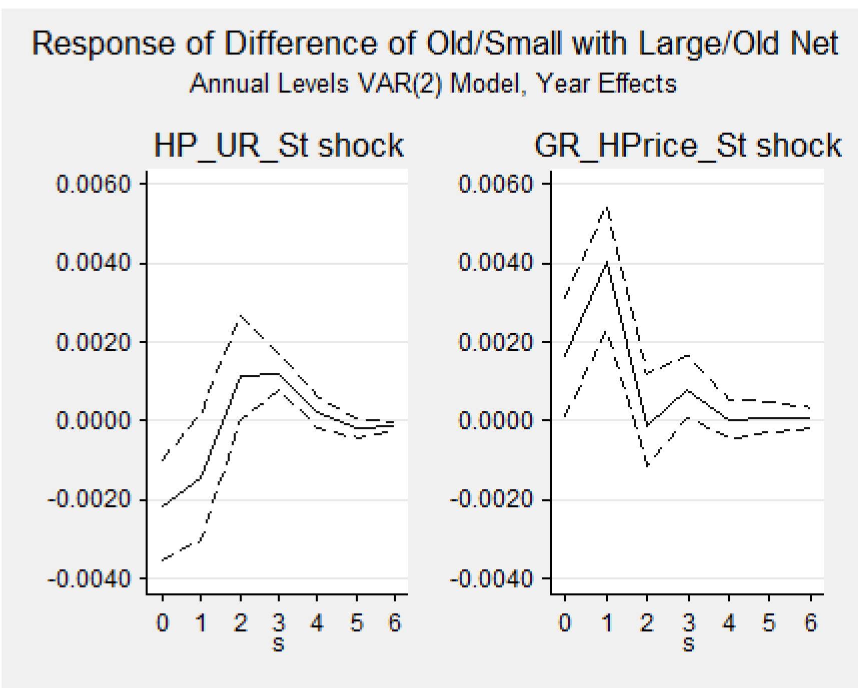


Figure A.1.6.a Putting State Housing Prices Last in Causal Ordering

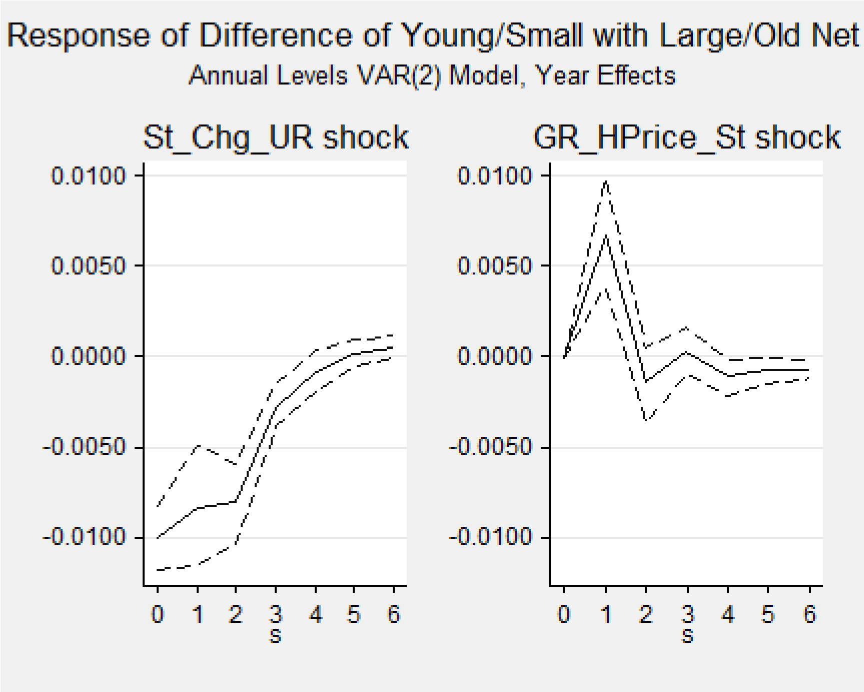


Figure A.1.6.b Putting State Housing Prices Last in Causal Ordering

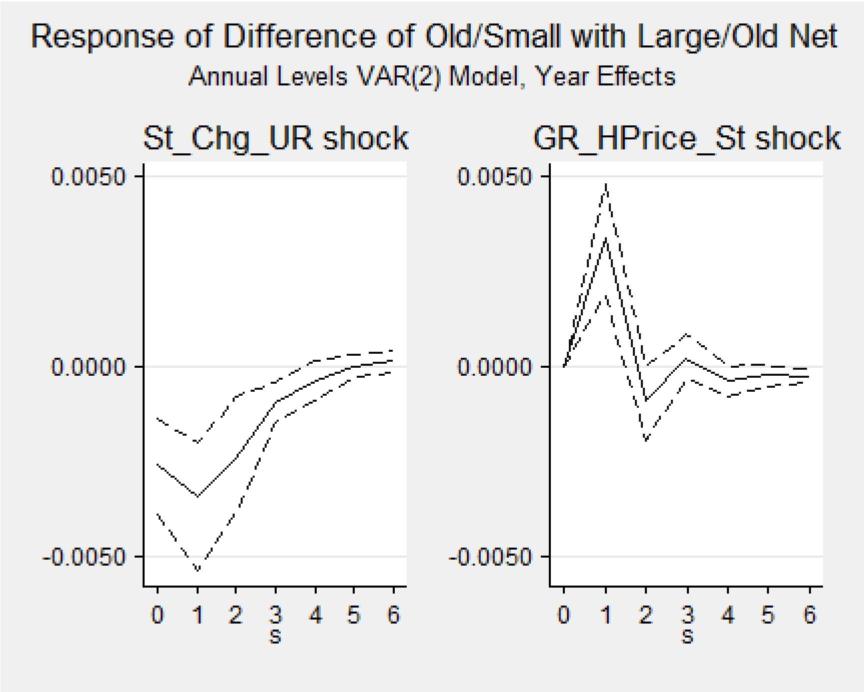


Figure A.1.7 Using Initial Size

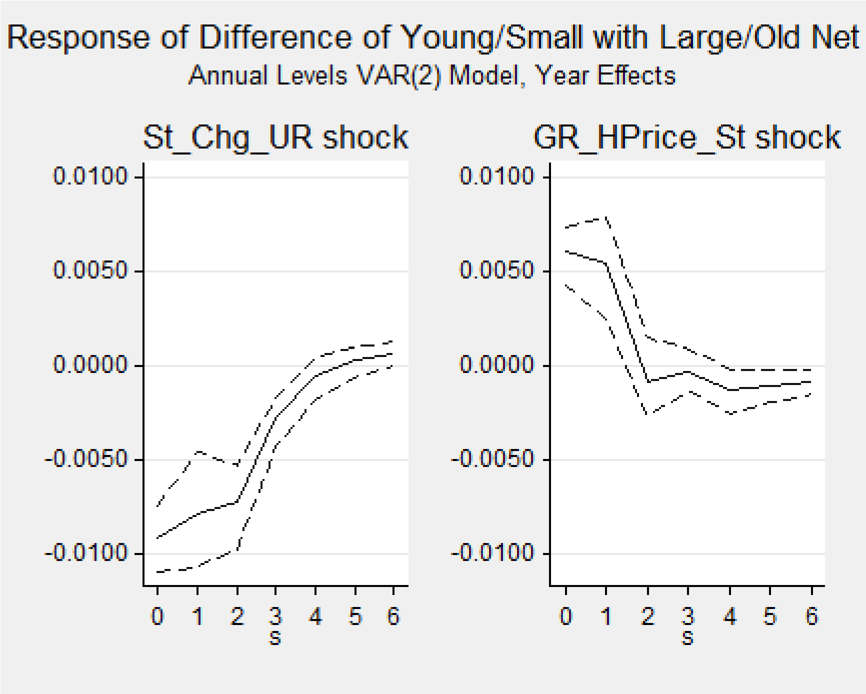


Figure A.1.8 Job Creation Differential Response for Young/Medium

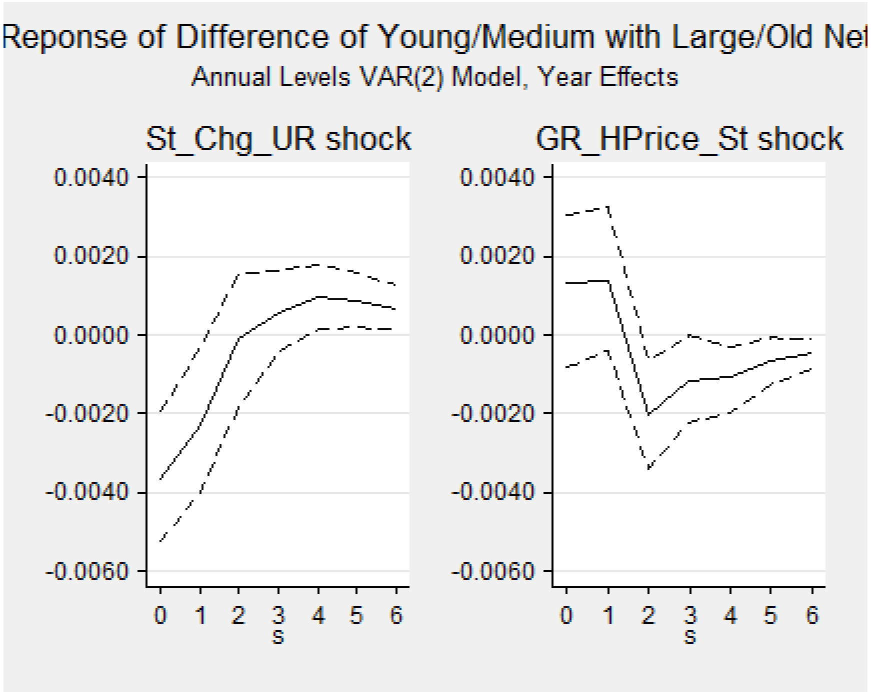


Figure A.1.9 Job Destruction Differential Response for Young/Medium

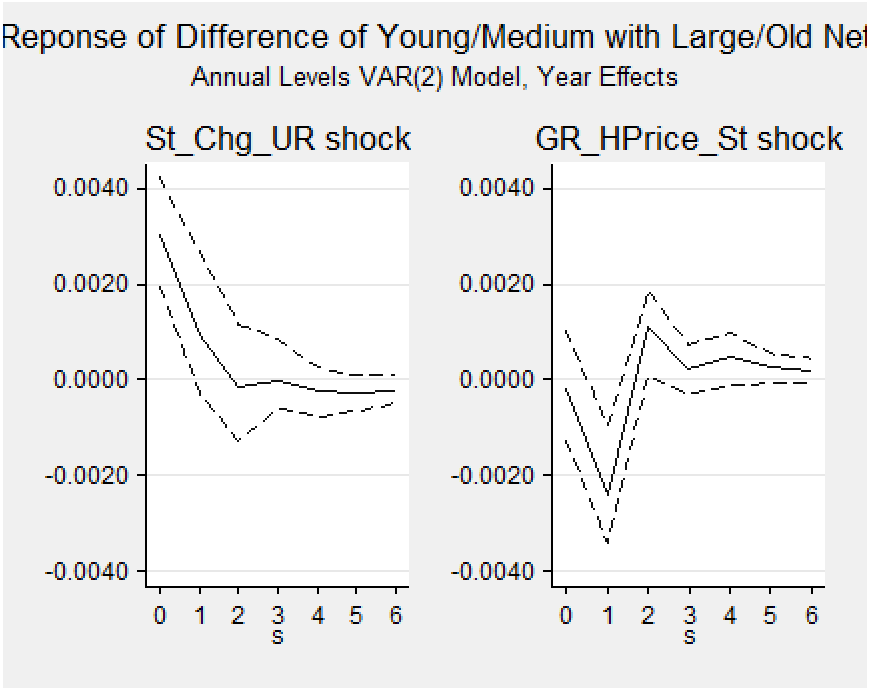


Figure A.1.10 Using only Firm Age, Net Differential Response for Young (<5) Minus Old (5+)

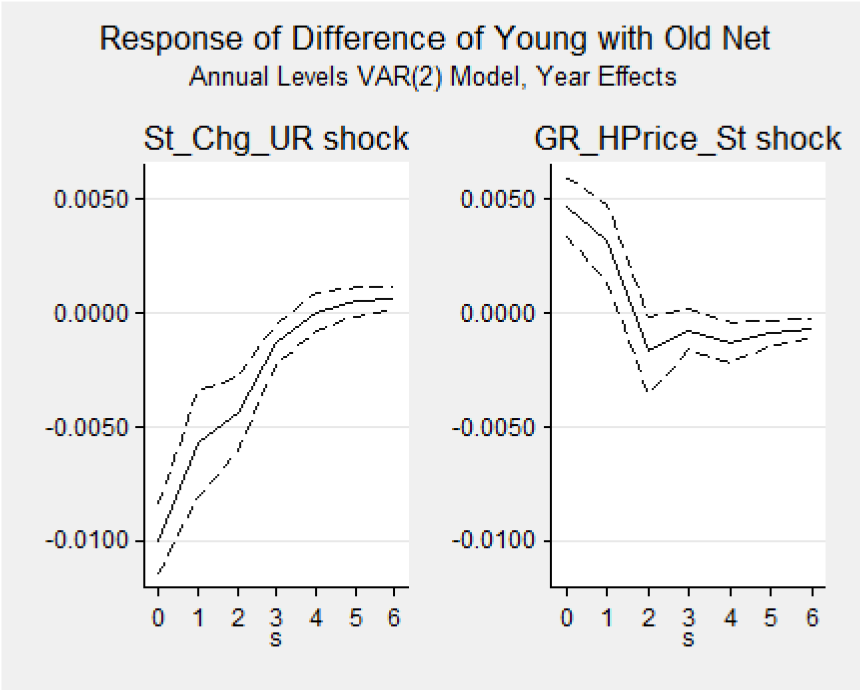


Figure A.1.11 Using only Firm Size, Net Differential Response for Small/Medium (<500) Minus Large (500+)

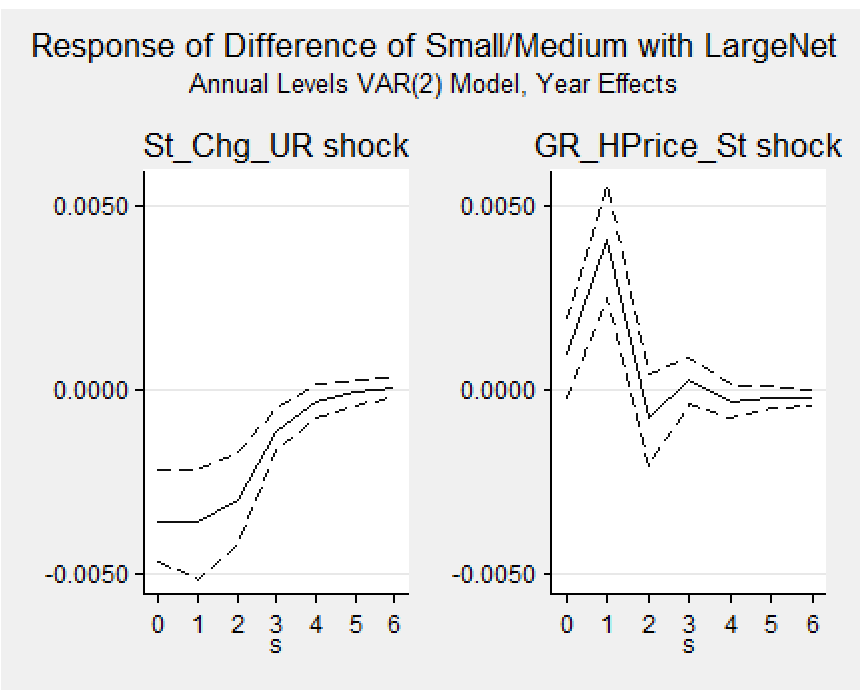


Figure A.1.12 Using Real GDP Growth Rates

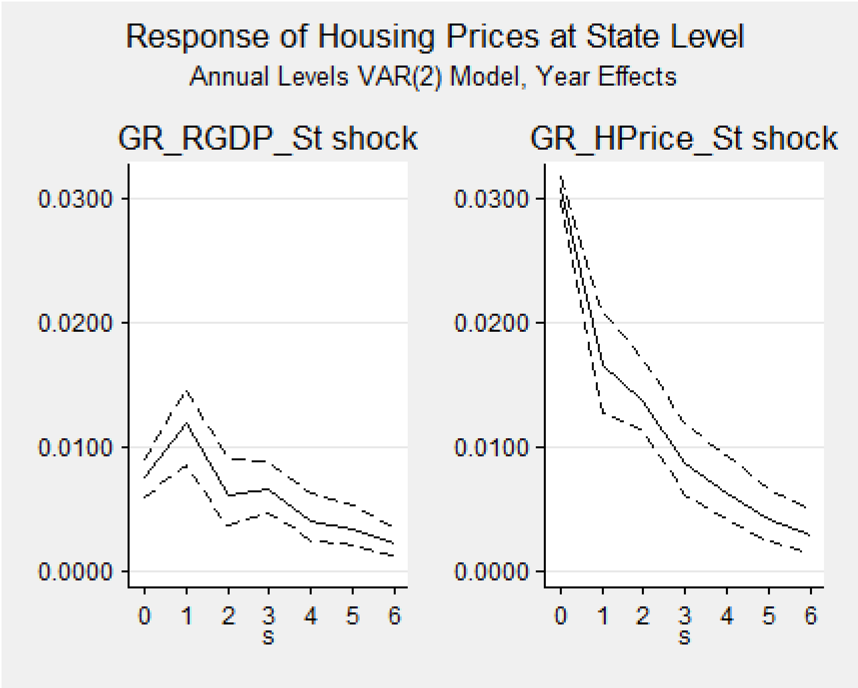


Figure A.1.13 Using Real GDP Growth Rates

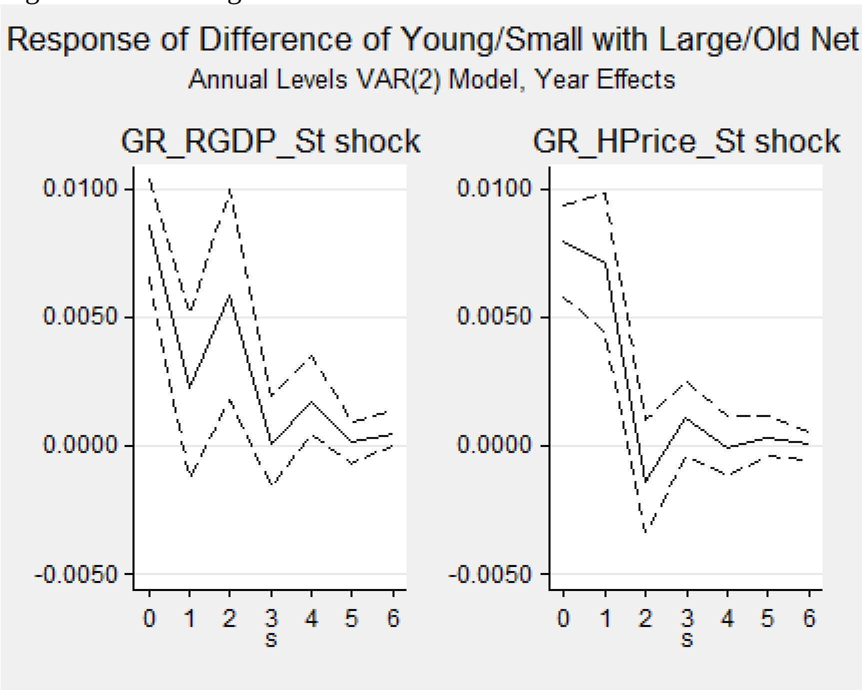


Figure A.1.14 Using Real GDP Growth Rates

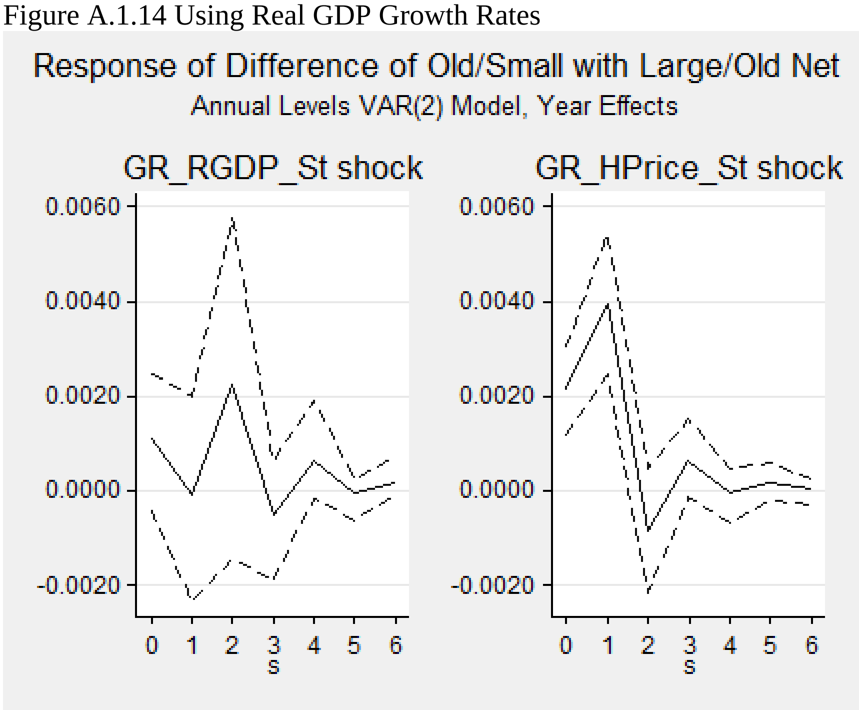


Figure A.1.15 Using Real Personal Income Growth Rates

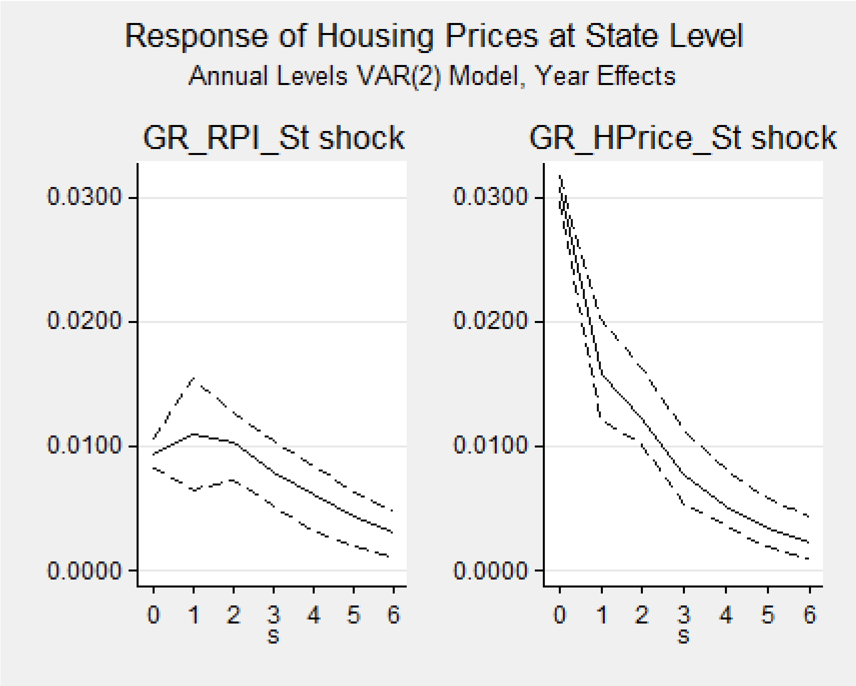


Figure A.1.16 Using Real Personal Income Growth Rates

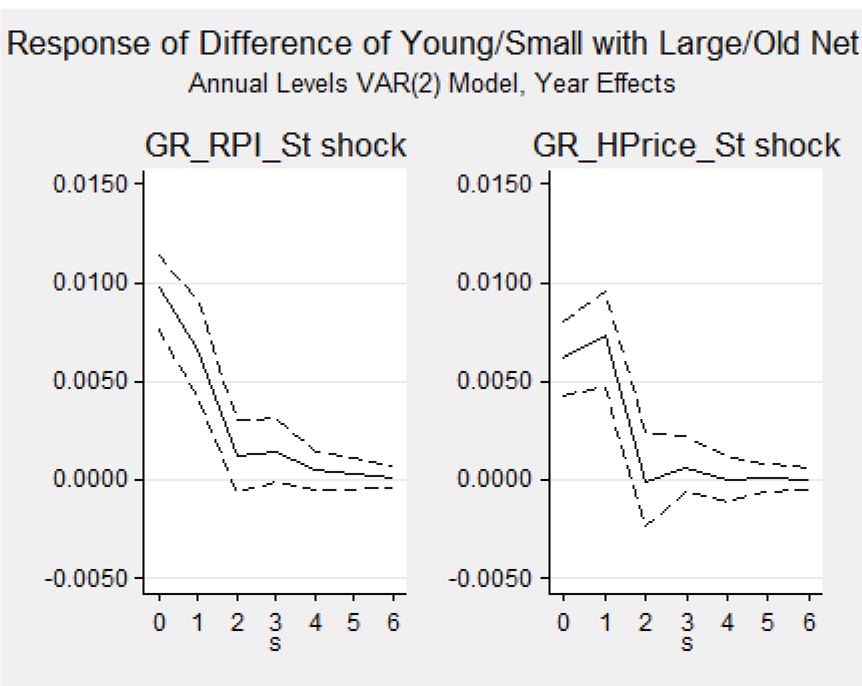


Figure A.1.17 Using Growth Rates in Real Personal Income

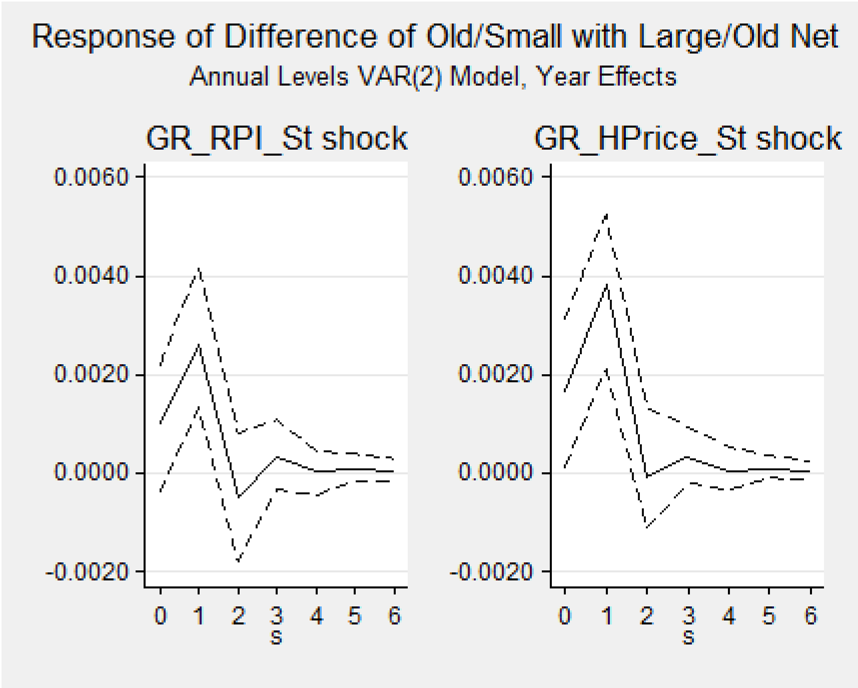


Table A.1. Descriptive Regressions at the National Level Using Real GDP

	(1) Net_Rate_All	(2) net_rate_11	(3) net_rate_21	(4) net_rate_12	(5) net_rate_22	(6) net_rate_32
Real GDP Growth	0.821***	1.087***	0.880**	0.480*	0.820***	0.710***
	(0.108)	(0.269)	(0.285)	(0.179)	(0.158)	(0.130)
Int_Rt_Sprd	-0.481*	-0.317	-1.037*	-0.227	-0.603*	-0.475*
	(0.185)	(0.460)	(0.487)	(0.306)	(0.271)	(0.222)
GR_HPrice_st	0.023	0.466**	0.308*	0.117	0.038	-0.024
	(0.052)	(0.130)	(0.137)	(0.086)	(0.076)	(0.063)
N	30	30	30	30	30	30

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.2 Correlations Between Cyclical Indicators and Net Differential Employment Growth Rates (Using Initial Size)

	Change in Unemp Rate		Net Emp. Growth Rate		Real GDP Growth		HP Filtered Unemp Rate	
	1981-2010	1981-2006	1981-2010	1981-2006	1981-2010	1981-2006	1981-2010	1981-2006
Young/Small-Older/Large	-0.448	-0.302	0.557	0.272	0.548	0.345	0.268	0.232
	(0.013)	(0.134)	(0.001)	(0.180)	(0.002)	(0.085)	(0.152)	(0.255)
Young/Medium-Older/Large	-0.322	-0.247	0.453	0.249	0.327	0.306	0.121	-0.051
	(0.083)	(0.224)	(0.012)	(0.220)	(0.078)	(0.129)	(0.523)	(0.805)
Older/Small-Older/Large	0.163	0.312	0.037	-0.237	0.030	-0.185	0.564	0.594
	(0.389)	(0.121)	(0.845)	(0.244)	(0.875)	(0.365)	(0.001)	(0.001)
Older/Medium-Older/Large	-0.21	-0.085	0.395	0.243	0.437	0.187	0.415	0.544
	(0.266)	(0.680)	(0.031)	(0.233)	(0.016)	0.361	(0.023)	(0.004)

Note: P-values in parentheses.

Table A.3 Descriptive Regressions at State Level, Using the Net Employment Growth Rate at state level as the cyclical indicator (Controlling for State and Year Fixed Effects)

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
net_rate_st	0.559^{***}	0.224^{***}	-0.241^{***}	-0.209^{***}
	(0.058)	(0.068)	(0.038)	(0.038)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
net_rate_st	0.444^{***}	0.182^{*}	-0.320^{***}	-0.263^{***}
	(0.061)	(0.072)	(0.040)	(0.040)
GR_HPrice_st	0.165^{***}	0.061	0.115^{***}	0.078^{***}
	(0.028)	(0.034)	(0.019)	(0.019)
N	1530	1530	1530	1530

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium. All net differentials are with respect to Old/Large.

Table A.4 Descriptive Regressions at State Level, Using the Change in Unemployment Rate at state level as the cyclical indicator (Controlling for State Fixed Effects Only)

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
Chg_UR_st	-1.719^{***}	-1.046^{***}	0.219^{*}	-0.409^{***}
	(0.135)	(0.147)	(0.088)	(0.074)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
Chg_UR_st	-1.131^{***}	-0.699^{***}	0.421^{***}	-0.303^{***}
	(0.138)	(0.156)	(0.093)	(0.079)
GR_HPrice_st	0.309^{***}	0.182^{***}	0.106^{***}	0.055^{***}
	(0.026)	(0.030)	(0.018)	(0.015)
N	1530	1530	1530	1530

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium. All net differentials are with respect to Old/Large.

Table A.5 Descriptive Regressions at State Level (Controlling for State and Year Fixed Effects) – Using State-Level Change in Unemployment Rate as Cyclical Indicator and Initial Firm Size

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
Chg_UR_st	-2.168***	-1.530***	-0.600***	-0.659***
	(0.195)	(0.271)	(0.136)	(0.137)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
Chg_UR_st	-1.846***	-1.496***	-0.495***	-0.596***
	(0.195)	(0.277)	(0.139)	(0.140)
GR_HPrice_st	0.203***	0.022	0.066***	0.039*
	(0.025)	(0.035)	(0.018)	(0.018)
N	1530	1530	1530	1530

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium. All net differentials are with respect to Old/Large.

Table A.6 Descriptive Regressions at State Level, Using the Real GDP Growth Rate at state level as the cyclical indicator (Controlling for State and Year Fixed Effects)

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
GR_GDP_st	0.338***	0.158***	0.029	0.036
	(0.040)	(0.047)	(0.027)	(0.026)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
GR_GDP_st	0.246***	0.127*	-0.008	0.018
	(0.042)	(0.050)	(0.028)	(0.028)
GR_HPrice_st	0.171***	0.057	0.068***	0.033
	(0.029)	(0.034)	(0.019)	(0.019)
N	1530	1530	1530	1530

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium. All net differentials are with respect to Old/Large.

Table A.7 Descriptive Regressions at State Level, Using the Real Personal Income Growth Rate at state level as the cyclical indicator (Controlling for State and Year Fixed Effects)

Bivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
GR_RPI_st	0.658***	0.391***	0.114*	0.068
	(0.066)	(0.078)	(0.044)	(0.044)

Multivariate

	(1) diff_net_rate_11	(2) diff_net_rate_21	(3) diff_net_rate_12	(4) diff_net_rate_22
GR_RPI_st	0.499***	0.375***	0.045	0.030
	(0.076)	(0.089)	(0.051)	(0.050)
GR_HPrice_st	0.133***	0.014	0.057**	0.032
	(0.031)	(0.036)	(0.021)	(0.020)
N	1530	1530	1530	1530

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ Note 11=Young/Small, 21=Young/Medium, 12=Old/Small, 22=Old/Medium. All net differentials are with respect to Old/Large.