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Satellite-based measures of buildout and the effect of constrained housing supply on regional labour markets

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Abstract

We examine the impact of housing supply restrictiveness on regional adjustment to labour market shocks in New Zealand. To do so, we develop a measure of city-level housing supply restrictiveness that combines a novel satellite-based measure of suburban buildout with extant estimates of implicit regulation costs and geographic constraints on land. We incorporate the new measure of housing supply restrictiveness into an empirical model of regional adjustment that describes metropolitan labour and housing market outcomes. Our results show that after a positive labour market shock, regions with relatively restrictive housing supply experience lower employment and population growth; less housing construction; and greater increases in rents compared to regions with responsive housing supply.

Keywords: Regional Adjustment, Housing Supply, Buildout, Satellite Imagery, Labour Markets.

JEL Classification: J61, R23, R30, C33

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1 Introduction

From time to time regions are subjected to exogenous economic shocks. The extent to which regional labour markets are able to absorb and adjust to these shocks is largely predicated on their ability to foster regional migration of workers and firms (Blanchard and Katz, 1992; Decressin and Fatás, 1995; Dao et al., 2017). Recoveries from downturns are driven by households out-migrating to more prosperous regions and firms in-migrating to create jobs and take advantage of the surplus of unemployed labour. Economic booms are similarly mediated through household and firm responses, with households in-migrating to take advantage of higher wages, while local firms potentially out-migrate, downsize or shut down as labour costs increase.

Housing supply mediates the responses to these economic shocks. Construction of new housing is required to accommodate an in-migrating workforce, but restrictive housing supply constrains the ability of a region to retain workers over the long run (Glaeser and Gyourko, 2005; Saks, 2008; Zabel, 2012; Moretti, 2013). If housing supply is highly inelastic, economic expansions will push up rents, eroding the incentive for workers to in-migrate. This adversely impacts economic growth for the region and erodes efficiency gains from agglomeration for the economy as a whole if the most productive areas have inelastic housing supply (Hsieh and Moretti, 2019; Nunns, 2019).

In this paper we examine how regional variation in housing supply restrictiveness impacts regional adjustment to labour market shocks in New Zealand. To do so, we follow Saks (2008) and Zabel (2012) and incorporate measures of housing supply restrictiveness into a structural VAR model of regional adjustment in the tradition of Blanchard and Katz (1992). These authors use the Wharton Residential Land Use Regulation Index (WRLURI) (see Gyourko et al., 2008) to assign metropolitan regions within the US a measure of housing responsiveness that equates to a housing supply elasticity. However, because no such measures exist for New Zealand, our first step in this process is to create estimates of housing supply elasticities for the country's metropolitan areas. This measure of restrictiveness combines estimates of land price distortions arising from land use restrictions (LURs) (Glaeser and Gyourko, 2002), geographic constraints on physical land capacity (Saiz, 2010), and the proportion of developable land that has already been urbanized, which we refer to as a measure of buildout.[1] For the latter, we propose a novel estimation technique based remotely-sensed light spectrum data to discriminate between developed and undeveloped land in satellite imagery of the metropolitan area.[2]

We incorporate this variation in regional housing supply elasticities into a structural VAR model of regional adjustment that describes regional labour and housing market outcomes. Within the model, households (firms) are attracted to (repelled from) regions with relatively low unemployment,

[1] "Buildout" refers to the point at which development has reached a city's borders or has exhausted large-scale greenfield options (Lang & LeFurgy, 2007). Measures of buildout provide a relative estimate of how close the city is to exhausting remaining land and reaching buildout.

[2] 'Remotely sensed data' refers to geospatial data collected from aerial or satellite based sensors.

and repelled from (attracted to) regions with relatively high unemployment. These endogenous labour demand and supply responses thereby equilibrate the incidence of labour market shocks on wages and unemployment across different geographic regions. Housing markets mediate the endogenous household migration response is in the adjustment process. The models are fitted to annual data spanning 2000 to 2016 and labour market shocks are identified using shift-share instruments (Bartik, 1991; Card, 2001).

Our results show that metropolitan areas with more restrictive housing supply retain fewer workers over the long run in response to a positive labour market shock (either supply or demand). For example, after a labour demand shock, cities with restrictive housing supply retain only 27% of the jobs created over the long-run. In contrast, cities with less restrictive housing supply retain 56% of the jobs created. Thus there is much more job destruction in areas with restrictive housing following a positive economic shock. In addition, the response of construction permits and rents to these shocks is consistent with housing supply mediating these long run population responses. In cities with restrictive housing supply, there is less construction and more appreciation in rental prices compared to cities with responsive housing supply. Interestingly however we find that house prices are largely unresponsive to these labour market shocks, which is consistent with earlier studies of regional adjustment in New Zealand (Grimes et al., 2009).

This paper makes several contributions to the existing literature. First, it proposes and applies a new method to estimate buildout constraints in metropolitan areas. The method is based on a normalized vegetation difference index (NVDI) that uses satellite imagery of metropolitan regions to differentiate between intensified and undeveloped land. Although our application is to New Zealand data, the method should be of interest more broadly to urban economists and geographers. Second, it shows that restrictions on housing supply adversely impact regional economic growth in New Zealand. While there is a developing literature demonstrating this in the US (Hsieh and Moretti, 2019), there is as yet little research demonstrating this in the NZ context. This finding should be of particular importance to domestic policy makers at both the local and national levels.[3]

The remainder of the paper is structured as follows. Section two outlines the related literature on both regional adjustment and empirical measures of housing supply restrictiveness. Following this, the modelling approach and data are outlined in sections three and four, respectively. Section five presents the empirical results, followed by a discussion. Section six concludes.

[3] For instance, New Zealand has a recently established 'Provincial Growth Fund' which has earmarked $1 billion of crown funds annually for investment in New Zealand provinces. Most likely these funds will be focused on stimulating regional job growth. However, the extent to which this translates to long run employment opportunities and population growth will be dependent on the ability of regions to accommodate new workers through the housing channel.

2 Related Literature

This paper builds on two related literatures: measures of housing supply restrictiveness and empirical models of regional labour market adjustment. We discuss how this paper relates to each.

Empirical measures of restrictions on housing construction have received increasing attention over the past two decades. We group these measures into four categories: (i) measures of exogenous geographic constraints on land; (ii) measures of buildout (i.e. the proportion of developable land that has been developed); (iii) measures based on textual analyses of land use regulations; and (iv) inferred measures of land use regulations based on transaction price data. Saiz (2010) provides the preeminent example of (i) by using detailed geospatial datasets to estimate the amount of land in metropolitan areas that is suitable for development – that is, not foregone to water or steep terrain. Extant examples of (ii) include Hilber and Vermeulen (2016), who identify buildout based on GIS overlays, and Paciorek (2013), who uses census tract data on dwellings. Our proposed satellite-based method for estimating buildout falls into this category and should be applicable to any urban or suburban region given the proliferation of satellite imagery that is readily available. Examples of (iii) include Saks (2008) and Gyourko et al. (2008). Saks (2008) develops an index based on six different land use surveys sent to local and higher level government officials that questioned them on the prevailing planning regulations in their respective jurisdictions. Gyourko et al. (2008) develop the Wharton Residential Land Use Regulatory Index (WRLURI) based on a country-wide survey of 2000 local planning jurisdictions in the USA. Examples of (iv) include Glaeser and Gyourko (2003), who estimate the stringency of land use regulation through the comparison of the extensive and intensive price of land using on individual-level property information. Grimes and Liang (2009) focus on price differentials in land on either side of the urban-rual boundary to infer the impact of the boundary on housing supply. Many papers combine the various methods. For example, Saiz (2010) augments measures of regulatory restrictions with measures of the amount of land suitable for development when generating empirical proxies of housing supply elasticity. We combine measures that fall into (i), (ii) and (iv).

This paper also relates to a larger literature on empirical models of regional adjustment. Blanchard and Katz (1992) provide the canonical model of regional adjustment fitted to US states. In the model, workers are attracted to regions with high wages and low unemployment, while firms are attracted to regions with low wages and high unemployment. The empirical model decomposes variation in employment, labor force and population into labor market shocks, thereby revealing the role of household mobility in adjustment to regional labor market shocks. The framework has since been applied to many other countries and regions (Jimeno and Bentolila, 1998; Fredriksson, 1999; Debelle and Vickery, 1999; Tani, 2003; Fidrmuc, 2004; Bornhorst and Commander, 2006; Sala and Trivin, 2014; Choy et al., 2002; Grimes et al., 2009; Beyer and Smets, 2015). However, as pointed out by Greenaway-McGrevy and Hood (2016), impulse responses must be carefully constructed when using the model to infer the contribution of household mobility to regional recoveries and adjustments. We follow their approach of modelling the response to a serially-uncorrelated shock. We also extend the basic BK framework to examine how differences in housing construction restrictiveness impact regional adjustment channels. Saks (2008), Zabel (2012), and Greenaway-McGrevy and Hood (2016) each examine the extent to which the elasticity of housing supply impacts long run regional responses to economic shocks in the US, typically finding that restrictive housing supply impedes household migration.

3 Using Satellite Imagery to construct Measures of Buildout

In this section we describe our proposed method for estimating buildout based on satellite imagery of the earth's surface. We then compare this measure to two other commonly used measures that can also be readily computed based on available data. Together with the satellite based measure of buildout, these additional measures comprise our index of housing supply restrictiveness.

Buildout is the proportion of developable land that has been developed within a given radius of the city centre. Housing supply restrictiveness is increasing in this proportion as more buildout implies a smaller proportion of undeveloped land that is available for future urban housing development. In regions where there is less undeveloped land suitable for urban development, developers must instead assemble parcels of developed land in order to teardown and redevelop the properties into more intensive housing structures (duplexes, terraced housing and apartments). This entails significant land assembly costs (O'Flaherty, 1994). Furthermore, the land may be relatively more expensive to develop, with a lower return, as it may not be proximate to existing infrastructure and amenities such as employment centres, schools and retail shopping areas. Buildout has been utilized as measures of supply restrictiveness in previous research such as Paciorek (2013), Hilber and Vermeulen (2016) and Nunns (2019).

The new method we propose is based on a normalized vegetation difference index (NVDI), which uses light spectrum analysis from remotely sensed images to differentiate between intensified land and undeveloped land. An NDVI differentiates land area by it's foliage coverage, permitting discrimination between urbanized (non-permeable land area such as concrete and structures) and undeveloped (permeable) greenfield areas. The approach follows from a growing economic literature that integrates elements of the geographic and economic sciences by utilizing remotely sensed data (see Donaldson and Storeygard, 2016, for a review). To the authors' knowledge, the extent of NDVI usage in the economics literature has been confined to only a handful of studies focusing predominantly on the field of agricultural economics, where it is a useful measure for land production yields. Several recent studies outside of the economics literature have also utilized NDVI in hedonic modeling as measures of neighborhood green space (Li et al., 2015; Mei et al., 2018).

The NVDI exploits the fact that plants absorb visible light in order to photosynthesize, while plant cell structure reflects infra-red light. Calculation of the NDVI therefore relies on the availability of geospatial raster image data that measures the proportion of visible and (invisible) near infra-red light reflected by the surface of the earth. Let $l = 1, ..., L$ index pixels in the raster image for a pre-defined area. NVDI is calculated for each pixel l as:

$$NDVI_l = \frac{NIR_l - RED_l}{NIR_l + RED_l} \tag{1}$$

where NIR_l is the proportion of near infrared light reflected and RED_l is the proportion of visible light reflected. Low values indicate areas barren of foliage cover and high values indicate areas of high foliage cover. By construction, $NDVI_l \in [-1, 1]$, with higher values representing areas areas reflecting wavelengths of red and NIR light consistent with live vegetation. We set the threshold for identifying live vegetation to be 0.35, meaning that any pixel with a $NDVI_l$ value over 0.35 is classified as representing greenfields area which is yet to be developed. A value below 0.2 is considered to represent area devoid of vegetation and a value of 0.5 represents full vegetation (see Sobrino et al., 2001). The total undeveloped area is given as the sum of the number of pixels within a predefined area L:

$$L(G) = \sum_{l \in L} \mathrm{I}_{NDVI_l > 0.35}$$

where $\mathrm{I}_{NDVI_l^i > 0.35}$ is an indicator function equal one when $NDVI_l$ exceeds 0.35 and zero otherwise. The proportion of undeveloped land is then given by $L(G)/L$ and buildout is $1 - L(G)/L$. To demarcate L we use a modification of the Saiz (2010) method for identifying developable land around a city centre. As described in more detail in section 3.1.2 below, the approach is based on the area of land within 25 km of the city centre that is suitable for development.

The data required for the NDVI computation is obtained through the United States Geological Survey (USGS) database in the form of 30m resolution images for both the red (visible) and near infrared spectrum. Each pixel therefore represents the same amount of land area (30 m^2). The images were captured by the LandSat 7 imaging satellite during the period August to September 2000.[4] We use these two months in order to ensure consistency in seasonal variation of vegetation. Performing the analysis for spring months mitigates issues arising from seasonally dry conditions that make it difficult to differentiate permeable and impermeable land coverage. In addition, we ensure that each raster image has less than 5% of cloud coverage.

The obtained raster images are collated into mosaic form using the GIS platform ArcMAP and the NVDI is computed from this to ensure consistency in the index limits for the entire sample of New Zealand regions. The raster images are then cropped by the Saiz 25km-radius overlays which remove areas of challenging terrain and geography off-limits to residential development. The images are then classified by NDVI values reflecting urban and undeveloped land areas.

[4] Data used in our empirical application begin in 2000.

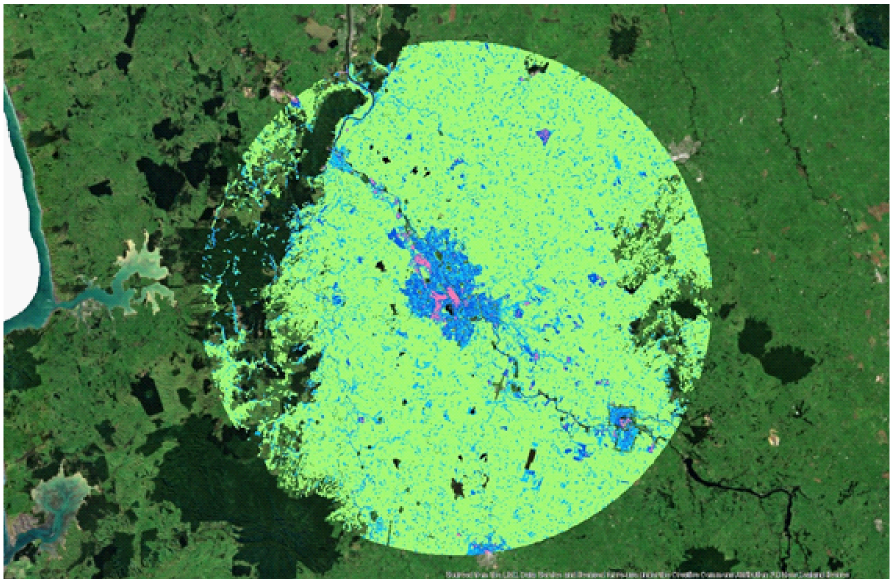

Figure 1: A processed form of the NDVI for Hamilton, New Zealand classified by 4 bands. Fuchsia highlights the areas of intensely developed area and blues are indicative of lower intensity urban development. Green represents undeveloped area.

Figure 1 represents an example of a processed NVDI image for Hamilton, New Zealand, with thresholds for urbanized and greenfield areas. In this image green represents areas of permeable area (undeveloped land) and the fuchsia and blue areas represent intensified areas (buildout). Hamilton is instructive as an example of a city largely unconstrained by its surrounding topography: it is inland and lies on a plain.

Although we apply the method to New Zealand towns and cities, we expect the method to be easily generalizable to other countries given that the requisite satellite imagery is freely available and easily accessed online. However, the threshold for vegetation might need calibration based on the surrounding ecology of the suburban area. For example, more arid regions may have a lower threshold for identifying vegetation, and the method may not be applicable to cities located in deserts.

3.1 Extant Measures of Housing Supply Restrictiveness

We compare the satellite-based measures of buildout to two other commonly used measures of housing supply elasticity that can be calculated based on the data available. These are the Glaeser and Gyourko (2003) measure of regulatory distortion and the Saiz (2010) measure of developable land. Our final index of housing supply restrictiveness is based on an average of the three different measures.

3.1.1 Regulatory Distortions

Glaeser and Gyourko (2003) suggest that land use restrictions which act to limit the supply of housing manifest as a discrepancy between the intensive and extensive price of land. It can be estimated using hedonic decompositions of house sales transaction data in combination with estimates of total land value of each parcel. To fix ideas, their approach can be formalized in the following model

$$P(L) = T + K + pL \tag{2}$$

where $P(L)$ is the price of a property expressed as a function of land L, K is the the capital value of any improvements on the respective properties, T are implicit "taxation" costs T resulting from LURs, and p represents the market price of land at the margin. T represents any factors that drive a wedge between prices and constructions costs – primarily land use regulations which constrain the provision of new housing. Typical examples of these restrictions are minimum lot sizes, building height restrictions, coverage restrictions, and minimum parking requirements.[5] Glaeser and Gyourko (2003) note that caution must be given to interpreting the estimate of T as it cannot distinguish the effects of different LURs and is reliant on the assumption of a competitive construction sector.

In order to estimate T, we re-express (2) as follows

$$T = P(L) - K - pL$$

We can estimate the regulatory costs by comparing the extensive value of land $(P(L) - K)$ to the intensive value (pL). However, only $P(L)$ and L are observable from property transaction data, necessitating the estimation of K and p.

Glaeser and Gyourko (2003) estimate K via the use of building size characteristics and a construction cost price index series. However, in New Zealand each land parcel has an associated local government valuation which details the respective values of the land and capital improvement components, yielding a direct estimate of K.

To estimate p, Glaeser and Gyourko (2003) use a hedonic regression approach where observed (log) property transaction prices are taken to be a function of land area and a bundle of additional price-determining characteristics. We follow their approach. The hedonic specification we utilize

[5] The wedge may also embody the effects of geography to the extent that land use restrictions dictate the development potential of challenging terrain. However, the nature of the contribution is not understood well. Lees (2018) notes that tight geography is likely to increase demand for both the intensive and extensive land at the margin. Thus in interpreting his results he is disinclined to attribute a large impact to geographic constraints.

takes the form

$$p_q = \rho_0 + \rho_1 l_q + \rho_2' X_q + v_q$$

where q indexes transacted properties in the sample, l_q represents the natural log of land area for property q, and X_q is a vector of hedonic characteristics. Included in X_q are the (log) floor area, number of bedrooms and bathrooms, decade of construction, site intensity, indicators for whether the property has a deck attached, and indicators for internal or freestanding garages. Included also are dummy variables for building condition, appreciable views, and statistical area unit (SAU) in which the house is located.[6] The specification is estimated using a three-year window of property transactions which matches the three-year phasing of local government property valuation cycles.

The price distortion component T is then estimated as the average ratio of the estimated extensive value to the estimated intensive value. Specifically, the relative measure of the LUR price distortion can be constructed for each region i and time period t as:

$$R_{i,t} = Q^{-1} \sum_{q=1}^{Q} \frac{P(L)_{i,q,t} - K_{i,q,t}}{pL_{i,q,t}}$$

So-defined $R_{i,t}$ is increasing in T.

3.1.2 Estimates of Developable Land

Saiz (2010) estimates the (exogenously determined) amount of land that can be developed within a certain radius of an urban centre using GIS information on the terrain of the city, arguing that these geographic constraints on land restrict housing supply. He augments this measure with estimates of regulatory distortions in order to arrive at a measure of housing supply restrictiveness than incorporates both regulatory and geographic constraints to construction.

We replicate the approach proposed by Saiz (2010) but with some minor modifications. The first stage is to estimate the total amount of exogenous land supply surrounding the key urban center of the LMA. In general the approach follows that of Saiz (2010), however with several refinements. Firstly, we use a 25km radius around the urban centre of each LMA. This is done on the basis that metropolitan areas in New Zealand are generally much smaller than those in the USA. Secondly, in addition to the removal of inland water bodies and terrain with a greater than 15% slope, we also remove areas likely off-limits to future urban development, such as conservation areas (forests, waterfront area, etc.), along with areas designated as schools, public parks, recreation areas, historic sites, golf courses, and airports. Importantly, these factors can also be thought of as akin to land use regulation in the sense that they are the result of policy, not geography.

[6] SAUs are non-administrative geographic areas defined by Statistics NZ. Within residential urban areas, SAUs are typically a collection of city blocks or suburbs and contain 3,000-5,000 persons. For additional details see http://aria.stats.govt.nz/aria/#ClassificationView:uri=http://stats.govt.nz/cms/ClassificationVersion/cVYnMpeILgJRAY7E

We obtain the requisite geospatial data from several sources. 8m resolution Digital Elevation (DEM) data were obtained from the University of Auckland Geography Department. This raster based data was utilized to calculate terrain slope. Polygonal geospatial data for inland water bodies including lakes, streams and rivers was obtained from Land Information New Zealand (LINZ). Along with this, we also obtained polygonal data for regional and national parks, recreation areas, public schools, airports, and golf courses from LINZ.

3.1.3 Combined Index of Housing Supply Restrictiveness

In order to account for both regulatory and geographic constraints on housing construction, we construct an index that aggregates the three different measures of restrictiveness: the Glaeser and Gyourko (2003) extensive-intensive ratio of regulatory restrictions, the Saiz (2010) measure of developable land with a radius of the city centre, and our satellite measure of buildout within that radius.

The overall restrictiveness measure is calculated as the simple average of the three standardized indexes. This has the advantage of making the interpretation simple, with all positive (negative) values representing urban areas with higher (lower) than average levels of housing supply restrictiveness. We refer to resultant index as our 'combined measure'.

Table 1 ranks the LMAs by their respective combined measure of housing supply restrictiveness. Note that a lower rank value represents a relatively more restrictive environment. For instance, a L(T) rank of 1 indicates that the least amount of total developable land area surrounding the key urban center. Conversely, a rank of 22 indicates the urban center with the highest supply of developable land.

3.1.4 Comparison of the Different Measures of Housing Restrictions

Table 2 exhibits the correlations between the various measures and the combined index. The measures are reasonably correlated with one another. This is consistent with Saiz (2010), who notes that in the case of the USA, physical land availability measures are highly correlated with the WRLURI index.

We explore the ability of the different measures of housing restrictions to explain regional variation in house prices. Cities with more restrictive housing supply should have higher prices, ceteris paribus. Our exploratory regressions begin by regressing average regional house prices and rents on the different measures of housing restrictiveness in the year 2000. As shown in Table 3, the satellite based measure of buildout explains the most variation in the cross section of regional house prices. The satellite based measure also explains more variation in the change in house prices and rents

Table 1: Housing supply restrictiveness rankings for urban centres

Rank	Tertile	LMA	Urban Centre	ext/int	$L/(25^2\pi)$	$L(G)/L$	Combined Index
1	1	14	Lower/Upper Hutt	1	3	3	1.568
2	1	13	Wellington/Porirua	3	2	4	1.309
3	1	20	Queenstown	16	1	1	1.011
4	1	2	Auckland	5	12	2	0.863
5	1	21	Dunedin	7	6	8	0.595
6	1	16	Nelson	12	4	6	0.574
7	1	12	Paraparaumu	8	5	11	0.269
8	2	17	Blenheim	9	7	10	0.212
9	2	1	Whangarei	2	15	16	0.154
10	2	7	Gisborne	15	10	9	0.075
11	2	9	New Plymouth	4	11	21	0.071
12	2	5	Tauranga	13	9	12	0.026
13	2	15	Masterton	6	13	14	-0.033
14	2	18	Christchurch	10	18	5	-0.111
15	3	19	Timaru	11	19	7	-0.238
16	2	10	Wanganui	18	8	17	-0.375
17	3	8	Napier & Hastings	19	14	13	-0.517
18	3	11	Palmerston North	14	21	15	-0.958
19	3	4	Taupo*	20	17	18	-0.936
20	3	6	Rotorua	22	16	19	-1.160
21	3	3	Hamilton	17	22	20	-1.289
22	3	22	Invercargill	21	20	22	-1.463

$L/(25^2\pi)$ is the ratio of total developable land to total geographic area defined by a $25km$ radius. $L(G)/L$ is the ratio of undeveloped area to total developable area. Note that a lower rank value represents a relatively more restrictive environment. For instance, a L rank of 1 indicates that the least amount of total developable land area surrounding the key urban centre. Conversely, a rank of 22 indicates the urban centre with the highest supply of developable land. Note that we substitute the Timaru LMA for Taupo LMA in the estimations. This is on the basis that inclusion of Taupo in the least restrictive sample leads to spurious results in the responses to an employment demand shock.

Table 2: Correlations between different measures of housing restrictiveness

	ext/int	$L(T)$	$L(G)/L(T)$	CM
ext/int	1	0.52	0.57	0.79
$L(T)$	-	1	0.64	0.85
$L(G)/L(D)$	-	-	1	0.88
CM	-	-	-	1

CM denotes the combined index of housing supply restrictiveness. It is the average of the three measures after standardization.

between 2000 and 2016 than the two other measures explored. Nonetheless, we chose to employ the combined index in our empirical model of regional adjustment since both regulatory and geographic constraints on land have been shown to have an impact on regional adjustment mechanisms in other countries. Such regressions are also reduced-form and do not control for cross sectional variation in housing demand between locations.

4 Model

In this section we discuss how the measure of housing restrictiveness is incorporated into a conventional model of regional adjustment.

4.1 Conceptual framework

Our conceptual model relating housing supply restrictiveness to regional adjustment follows Saks (2008), which extends the standard BK framework to include housing markets. We discuss the intuition of the model here and relegate the set of mathematical equations describing the Saks (2008) model to the Appendix.

The BK model posits that labour migration between regions is based on workers maximizing utility by arbitraging real wages and amenities. Economic shocks then generate household migration between regions as households respond to changes in labor market price signals. Positive economic shocks generate in-migration of households and an out-migration of firms or jobs to other regions. Negative economic shock generate an out-migration of households and an in-migration of firms or jobs from other regions.

Local housing markets mediate the inbound and outbound movement of households. Inelastic housing supply elasticity limits housing construction, potentially resulting in lower in-migration and

Table 3: Explanatory power of various measures of housing restrictiveness

Dependent Variable	Regressor			
	GG Index	Saiz Index	SB Index	Combined Index
log mean house price 2000	0.0963	0.0679	0.2754	0.2065
log mean rental price 2000	0.1319	0.1120	0.3471	0.2849
log median house price 2000	0.1069	0.0796	0.3085	0.2332
log median rental price 2000	0.1263	0.0709	0.3061	0.2375
change in log mean house price, 2000-2016	0.0166	0.0100	0.1070	0.0352
change in log mean rental price, 2000-2016	0.0040	0.0034	0.0267	0.0094
change in log median house price, 2000-2016	0.0405	0.0010	0.1971	0.0774
change in log median rent price, 2000-2016	0.0014	0.0118	0.0521	0.0154

Tabulations of R^2s from regressions or various measures of housing expenses on various indexes of housing restrictions. SB denotes the satellite-based measure of buildout.

lower long-run employment in response to a positive economic shock (Saks, 2008; Zabel, 2012). Regions with tighter housing supply may find it difficult to attract new workers to the region following a positive employment demand shock due to the limited ability to build new houses. Inelastic housing supply also increases house price volatility (Paciorek, 2013), meaning that outbound migration after an economic downturn can be impeded by the lock-in effect of mortgage borrowing (Quigley, 1987), loss aversion (Genesove and Mayer, 2001), and the relatively low liquidity of property.

While many studies in the tradition of Blanchard and Katz (1992) focus on shocks to labour demand, exogenous variation in labour supply is also mediated by regional adjustment mechanisms. An exogenous in-migration of households to a specific region generates a surplus of labour in the region, providing an incentive for firms to in-migrate and households to out-migrate. The extent to which these households can be accommodated is mediated by the capacity of the housing stock to expand in response to the influx of households.

4.2 Empirical model

The BK model is conventionally specified empirically as a VAR. However, we follow Greenaway-McGrevy and Hood (2016) and specify the BK model as a panel VECM. The VECM spans the parameter space of the conventional VAR, but has the advantage of permitting us to construct impulse responses to a serially-uncorrelated labor market shock. Employment and population responses to a serially-uncorrelated shock can be used to decompose regional recoveries into household and firm migration channels. For example, after a negative labor demand shock, these responses tell us the proportion of the recovery in the regional unemployment rate that is due to household out-migration and the proportion of the recovery that is due to job creation. Responses to labor market shocks that exhibit serial dependence cannot be used to infer the relative contributions of migration and job creation. For further details, refer to Greenaway-McGrevy and Hood (2016).

The standard components of the modelling approach are (log) employment (e), population (p), labour force (l), and wages (w). In addition consideration is given to the effects of housing prices (hp) and rental prices (rp), along with new housing supply (hs) based on dwelling consent data. Then the following equation describes the empirical model

$$\Delta Y_{i,t} = \alpha_i + \delta_t + \beta Z_{i,t-1} + \textstyle\sum_{s=1}^{p} B_s \Delta Y_{i,t-s} + \gamma' W_{i,t} + \varepsilon_{i,t}$$

where $Y_{i,t} = (e_{i,t}, l_{i,t}, p_{i,t}, hp_{i,t}, rp_{i,t}, hs_{i,t})'$, $Z_{i,t} = (e_{i,t} - l_{i,t}, l_{i,t} - p_{i,t})'$, i indexes labour market area (LMA) designations, t indexes the time period, and α_i and δ_t represents LMA and time period fixed effects. Regional fixed effects account for regional differences in (time invariant) local amenities. Note that all endogenous variables are measured in log form. $W_{i,t} = \left(\epsilon^d_{i,t}, \epsilon^s_{i,t}\right)'$ is a vector of labour demand and supply shocks in the model and serve as the tool for estimating shock responses. The demand and supply shocks are both shift-shares (see Shock Identification section below). $Z_{i,t}$ represents the cointegrating vector and is recognizable as the employment ($e_{i,t} - l_{i,t}$) and participation rates ($l_{i,t} - p_{i,t}$).

The model is estimated on a sample of 22 labour market areas (see Data section below). To observe the impact of housing supply restrictiveness on regional adjustment mechanisms, we split the sample into tertiles based on the housing supply restrictiveness index. This yields 7 most restrictive and 7 least restrictive subsamples. This subsampling approach has been used by Zabel (2012), who uses deciles, and Saks (2008) and Greenaway-McGrevy and Hood (2016), both of whom use quartiles.

4.3 Shock Identification

We use Bartik (1991) shift-shares to recover labor demand and supply shocks from the reduced-form empirical model. The use of shift-share type instruments has proliferated across a broad range of literatures (Baum-Snow and Ferreira, 2014; Jaeger et al., 2018). These shift-shares are included as exogenous variables in the panel VECM.

Labor demand shift-shares in the tradition of Bartik (1991) combine national changes in sectoral employment with local-level sectoral concentration to impute changes in local labor demand. It is constructed as follows:

$$\epsilon^d_{i,t} = \sum_{j=1}^{J} \tfrac{E_{i,j,t-1}}{E_{i,t-1}} \cdot \left(\tfrac{\tilde{E}_{i,j,t} - \tilde{E}_{i,j,t-1}}{\tilde{E}_{i,j,t-1}} - \tfrac{E_t - E_{t-1}}{E_{t-1}} \right) \tag{3}$$

where i indexes the labour market area, j indexes industry, and t denotes the annual period. $\tilde{E}_{i,j,t}$ is national industry employment outside of MSA, i.e. $\tilde{E}_{i,j,t} = \sum_{i=1}^{n} E_{i,j,t} - E_{i,j,t}$, where $E_{i,j,t}$ is employment in industry j in region i in period t. Also, $E_{i,t} := \sum_{j=1}^{J} E_{i,j,t-1}$ and $E_{t-1} := \sum_{i=1}^{n} E_{i,t-1}$. The first term in (3) is the employment share of industry j in LMA i in period $t-1$ and the second term calculates the relative percentage change of employment in industry j across all other LMAs. The product of these is the degree to which labour demand in LMA i adjusts when affected by the same industry level trends across the country. The industry level employment data we utilize are categorized by a 3-digit Australian and New Zealand Standard Industrial Classification (ANZSIC) 2006 code.

Shift-shares based on regional immigration data are also increasingly used to isolate exogenous variation in labor supply. Originally employed by Card (2001), it has been used by Saiz (2003), Saiz (2007), Stillman and Maré (2008), Sá (2015), Gonzalez and Ortega (2013), Braakmann (2019) and Nunns (2019). Labor supply shift-shares are constructed following a similar approach to that of Saiz (2007), Paciorek (2013), and Nunns (2019). The supply shift-share is based international immigration from different source countries. It combines national immigration by country of origin with local-level concentration of immigrants by country of origin. The instrument is calculated as follows:

$$\epsilon_{i,t}^{s} = \sum_{k=1}^{K} \frac{P_{i,k,t-1}}{P_{i,t-1}} \cdot \left(\frac{\tilde{M}_{i,k,t} - \tilde{M}_{i,k,t-1}}{\tilde{P}_{i,k,t-1}} - \frac{M_t - M_{t-1}}{P_{t-1}} \right) \tag{4}$$

where i indexes the labour market area, and k indexes the country of birth of the migrant. $P_{i,k,t}$ denotes the population of persons residing in LMA i and born in country k in time period t. $\tilde{P}_{i,k,t}$ represents the total national population of persons born in country k residing in NZ but outside of LMA i, i.e. $\tilde{P}_{i,k,t} = \sum_{i=1}^{n} P_{i,k,t} - P_{i,k,t}$. $M_{i,k,t}$ represents the number of non-New Zealand citizen permanent long-term (PLT) arrivals born in country k moving to reside in LMA i in period t. $\tilde{M}_{i,k,t}$ is the total number of non-New Zealand citizen PLT arrivals born in country k intending to live outside of LMA i, i.e. $\tilde{M}_{i,k,t} = \sum_{i=1}^{n} M_{i,k,t} - M_{i,k,t}$. Also, $P_{i,t} := \sum_{k=1}^{K} P_{i,k,t}$, $P_t := \sum_{i=1}^{n} P_{i,t}$, and $M_t = \sum_{i=1}^{n} \sum_{k=1}^{K} M_{i,k,t}$. The first term of (4) is the population share of immigrants from country k residing in LMA i in period $t-1$. The second term is the relative increase in migrant inflows from country k for all other LMAs except i. The product of these gives an estimate of the exogenous change in labour supply in LMA i. The intuition behind the instrument is that a surge in immigrant inflows from a given source country is likely to reflect factors specific to that country and not prevailing local regional factors in location i. It also supposes chain-migration draws immigrants to certain regions more than others.

The supply shift-share is constructed based on census data and international permanent long term migration trends obtained from data captured at New Zealand ports of entry. The data details international migration by country of birth, citizenship, visa type, expected length of stay, intended LMA of residence, and age bracket.

Table 4: Data and Sources

Description	Years	Source
Working age population	2000-2016	Statistics NZ (Custom dataset)
Employment	2000-2016	Statistics NZ (Custom dataset)
Labour force	2000-2016	Statistics NZ (Custom dataset)
Wages	2000-2016	Statistics NZ (LEED series)
House Prices	2000-2016	CoreLogic NZ
Rental Prices	2000-2016	Ministry of Business and Innovation
Dwelling Consents	2000-2016	Statistics NZ (Regional indicators)
Shift-share demand	2000-2016	Statistics NZ (Custom dataset)
Shift-share supply	2000-2016	Statistics NZ (Custom dataset)

5 Data

The model is fitted to a sample of annual labour and housing market data spanning 22 Labour Market Areas (LMAs) over the 2000 to 2016 period. Table 4 provides an overview of the data employed.

All data are obtained at the Territorial Local Authority (TLA) level and aggregated up to LMA demarcations as detailed in Table 7 in the Appendix. Our LMAs demarcations are similar to those used in Nunns (2019), and we limit the sample to cities and towns with population over 10,000. The sample begins in 2000 due to the availability of the data used to make the shift-share variables.

The working age population, employment and labour force data are obtained from Statistics New Zealand. The population data is restricted to those persons aged between 15 and 64 years (inclusive). Hourly or similar normalized wage data is not readily provided by Statistics NZ at the TLA level. Instead the Linked Employer-Employee Database (LEED) series is utilized which provides aggregate earnings for all filled jobs.

House price data is obtained from a private New Zealand entity specializing in property market analytics (Corelogic New Zealand Ltd). The dataset consists of transaction data for each registered residential property sale in New Zealand between 2000 and 2016 and is cleaned to ensure data integrity. Using these data we construct a constant-quality hedonic imputed price index for each LMA. Refer to the Appendix for details.

Rental price data is sourced from the New Zealand Ministry of Business, Innovation, and Employment (MBIE). The dataset consists of mean rental prices across relatively fine geographic statistical areas and several categories of properties. Using this open access data, an annual hedonic imputation rental price index is constructed. The price indexes are more robust to quality changes than simple mean or median rental time series. Refer to the Appendix for details on construction of the indexes.

Housing construction is measured as the number of new residential dwelling consents within a TLA area during an annual period. This is obtained from Statistics NZ and is based on TLA level reporting of consenting activity. An important caveat is that these data are consented new dwellings and not completed builds. However, NZ lacks accurate and timely data on dwelling stocks. Consents for retirement village dwellings are removed as such dwellings explicitly cater for a demographic outside of the working age population of interest.

5.1 Preliminary diagnostic tests

We apply the Pesaran (2007) ('CIPS') panel unit root tests to the variables in the model. Results are tabulated in the Appendix. For (log) employment, population, labor force, wage, house prices, and rental prices variables, we accept the null of a unit root. After first-differencing the null of a unit root is rejected, indicating that the panels following unit root processes. For dwelling consents, the unit root hypothesis is rejected in several regions at the 10% level. This is unsurprising since consents represent a flow variable. Consequently each endogenous variable, except dwelling consents, enters the model in first differences. IRFs are cumulated to assess the long run effects on the levels of $I(1)$ variables in the system.

The lag order of the panel VECM is determined via use of the Lee and Phillips (2015) integrated likelihood information criterion (ILIC). The ILIC is a generalization of the standard Bayesian information criteria (BIC) and serves to correct for bias in ordinary least squares (OLS) estimation arising from biases due to the inclusion of incidental parameters (cross section fixed effects) in the model. The model selection criteria indicate a single lag model to be preferred. Thus all figures and tables related to the model results is that these are estimated using a lag order of one.

6 Results

In this section we present our empirical findings based on the fitted VECMs. Models are estimated using bias-corrected least squares to attenuate the $O\left(T^{-1}\right)$ Nickell bias in OLS estimators of dynamic panel models with cross section fixed effects (Hahn and Kuersteiner, 2002).

First we present the results from a model fitted to all 22 LMAs as a baseline comparison to sub-samples stratified by the combined housing supply restrictiveness index. These results also serve as a useful comparison to extant New Zealand regional adjustment studies and differs from this literature through the inclusion of the rental prices and the use of shift-shares for identification of labour demand and supply shocks. We then go on to present results from the model fitted to the highest and lowest tertiles when ordered by housing supply restrictiveness.

6.1 New Zealand regional labour market adjustment

We present and discuss impulse responses to labour demand labour supply shocks separately. Impulse responses at specific periods are tabulated in the Appendix (see Tables 6 and 7 in the Appendix).

6.1.1 Responses to a labour demand shock

Figure 3 exhibits impulse responses to a labour demand shock that generates a 1% increase in employment in the period of the shock. The initial 1% increase in employment is accounted for through a 0.72% increase in working-age population via in-migration, a 0.26% increase in the regional participation rate, and a 0.03% increase in the employment rate. The long-run change in employment, population, and labour force converges to a level of 0.51 after 5 years, implying that working age population permanently increases by 0.51% in the long run. This implies that approximately half of the jobs created by the initial demand shock are retained over the long-run, and thus firms and workers contribute equally to the regional adjustment process in the wake of the shock. Note that there is also a significant amount of out-migration in the periods subsequent to the shock, since working-age population decreases from 0.72 to 0.51 between periods one and five. These levels of long-run employment growth are only marginally higher than that previously estimated by Grimes et al. (2009) (0.51 versus 0.48), and are similar to Choy et al. (2002) and Grimes et al. (2009) in that the regional adjustment process following an economic shock is relatively swift in New Zealand.

Interestingly the response of house prices and wages to the shock is muted. The magnitudes and the sign of the wage response is consistent with that estimated by both Choy et al. (2002) and Grimes et al. (2009), while the house price response is consistent with Grimes et al. (2009), who find that the long run house price effects of a 1% labour demand shock to be a 0.05% increase.

However, in contrast to wages and house prices, we observe a large positive effect on rents and consents. Rents initially increase by 0.26% in the period of the shock before decreasing to arrive at a permanent increase by 0.2% over the long run. These patterns mimic the trends in working age population, which also initially overshoots relative to its long run level. Consents increase by 0.6% in the period of the shock. Thereafter the impact of the shock dissipates, although consents still remain 0.11% higher five years after the initial shock.

Figure 2: Impulse responses to a labour demand shock; all LMAs included in sample. Shock normalised to generate a 1% increase in employment. 90% confidence intervals given by dashed bands.

6.1.2 Responses to a labour supply shock

Figure 3 presents impulse responses to a labour supply shock that generates a 1% increase in employment in the period of the shock. We normalize to generate a one percent increase in employment – rather than population – to facilitate comparison with results from the labor demand shock.

The initial one percent increase in employment is accounted for through a 0.76% increase in working age population, a 0.33% increase in the participation rate and a 0.08% decrease in the employment rate. Thus not all of the influx of workers find employment, leading to an increase in the unemployment rate (equivalent to a decrease in the employment rate). The long-run responses are very similar to those exhibited for the labour demand shock: After 5 periods, the employment and participation rates have returned to pre-shock levels, and the employment, population, and labour force is approximately 0.57% higher. Firms and workers therefore contribute approximately equally to shock equilibration.

Turning to the housing market variables and wages, we observe similar patterns to those found for the case of the labour demand shock. There is a small, negative wage response and a lack of response in housing prices. Meanwhile, the labour supply shock generates an increase in rents and dwelling consents, although the rent response is smaller than that of the labour demand shock, while the dwelling response is larger.

6.2 Housing supply restrictiveness and regional adjustment

We now split the sample of 22 LMAs into tertiles according to measures of housing supply restrictiveness, and fit the model to the most and least restrictive tertiles. The sample split into tertiles reflects the limited cross sectional dimension of the panel.

6.2.1 Responses to a labour demand shock

Figure 4 illustrates responses to the labour demand shock. These responses are tabulated in the Appendix (Table A1).

There are distinct differences between the two sub-samples in the long run impact of the shock. In particular, there is less in-migration to cities with tight housing supply over the long run after a positive economic shock. In LMAs with more restrictive housing supply, the labor demand shocks generates a permanent 0.27 percent increase in employment and working age population. Thus only approximately 27% of the jobs created by the initial labour demand shock are ultimately retained. In regions with less restrictive housing supply, the shock generates a permanent increase in employment and working-age population of 0.56 percent, meaning that 56% of the jobs created by the initial shock are retained. As shown in Table 6 in the Appendix, the point estimate falls outside the 90% confidence interval of the population response of the restrictive supply sample. Regions with more responsive housing supply can therefore retain substantial more workers.

Figure 3: Impulse responses to a labour supply shock; all LMAs included in sample. Shock normalised to generate a 1% increase in employment. 90% confidence intervals given by dashed bands.

Figure 4: Responses to a labor demand shock in high (dotted) and low (solid) housing restrictiveness LMAs. Shock is normalised to generate a 1% increase in employment in the period of the shock.

The response of housing services (rents) and construction (dwelling consents) supports housing supply restrictiveness mitigating in-migration. In LMAs with low housing restrictiveness, we observe an immediate increase in construction, with dwelling consents increasing by 0.85 percent in the same period as the shock. This is slightly more that the 0.72 percent increase in working age population. Thereafter the impact of the shock on consents decreases. In contrast, we see a muted and sluggish response in LMAs with high levels of restrictiveness. In the period of the shock, dwelling consent increase by 0.22 percent. One year after the shock, we see a 0.31 percent increase in dwelling consents (relative to prior to the shock). Thereafter the dwelling response shrinks back to zero. Consistent with these supply responses, housing services increase more in LMAs with high housing supply restrictiveness than in LMAs with low restrictiveness. This evidence suggests that regions with tight housing supply constraints struggle to increase the housing stock to retain workers over the long-run in response to a positive economic shock. Note, however, that we do not observe substantial differences n house prices and wages between the two sub-samples. As illustrated and discussed in the previous section, wages and house prices appear unresponsive to labour market shocks in our sample.

Interestingly there are fewer differences between the two sub-samples in the initial incidence of the shock. The initial one percent increase in employment is primarily absorbed through in-migration in the sample period as the shock. In the low restrictiveness LMAs, the initial one percent increase in employment is accounted fro by a 0.67 percent increase in working age population, a 0.15 percent increase in the employment rate and a 0.16 percent increase in the participation rate. In high restrictiveness LMAs, one percent increase in employment is accounted fro by a 0.72 percent increase in working age population, a 0.06 percent increase in the employment rate and a 0.20 percent increase in the participation rate. However, over the long run, working population decreases by substantially more in high restrictiveness LMAs in the years after the initial shock. This may reflect churning in the household composition of the towns and cities, with in-migrating households displacing extant households to a greater degree in restrictive areas.

6.2.2 Responses to a labour supply shock

Figure 5 illustrates that responses to the labor supply shock are broadly consistent with the responses to the labour demand shock. Over the long run, we see a larger increase in employment, working age population and labour force in low housing supply restrictiveness LMAs. There is a permanent 0.45 percent increase in working age population in high restiveness LMAs and a 0.86 percent permanent increase in low restrictiveness LMAs. These estimates are statistically different from one-another at a ten percent significance level. In addition, there is a larger increase in dwellings and a smaller increase in rents in LMAs with low housing restrictiveness.

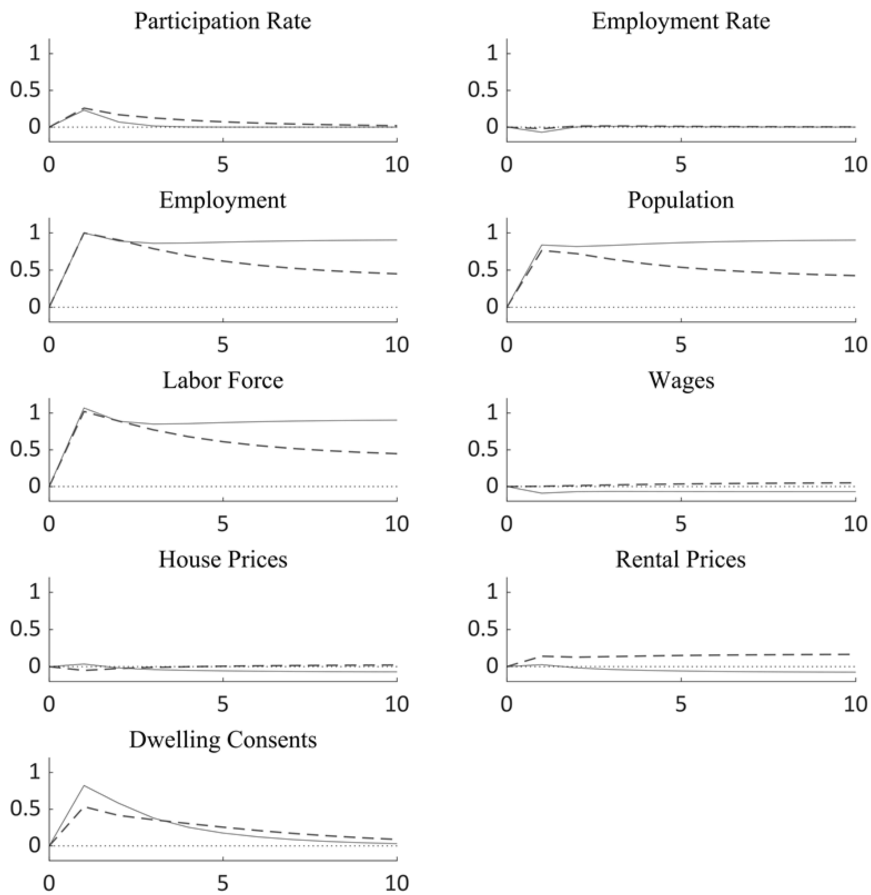

Figure 5: Responses to a labor supply shock in high (dotted) and low (solid) housing restrictiveness LMAs. Shock is normalised to generate a 1% increase in employment in the period of the shock.

6.3 Discussion

The effects of housing supply restrictiveness on regional adjustment are broadly in-line with the conceptual framework laid out by Saks (2008) and Zabel (2012). Specifically, regions with more inelastic housing supply experiencing a smaller long-run increase in employment and working age population than regions with less inelastic housing supply after a positive labor market shock. The response of rents and construction support housing elasticity mediating shocks, with regions with more inelastic housing supply experiencing a larger increase in rents and a smaller increase in construction.

We also find that housing supply frictions do not help us to understand the lack of house price and wage responsiveness already documented by the extant New Zealand regional adjustment literature (Choy et al., 2002; Grimes et al., 2009). Choy et al. (2002) consider a standard BK model incorporating only employment, population, labour force, and wage variables, showing that labor demand shocks generate large migration responses and relatively small wage effects. Grimes et al. (2009) extend Choy et al. (2002) and include house prices in the model, finding that house prices are unresponsive to employment demand shocks at the regional level. As Grimes et al. (2009) note, several factors could be responsible for house price unresponsiveness, all of which would apply to subsamples stratified by measures of regional housing elasticity. Firstly, the localized housing markets price movements may follow a singular national trend. Secondly, the LMA demarcations may be prohibitively large, washing out localized effects of employment demand on housing prices. Thirdly, Grimes et al. (2009) suggest that estimation may be hindered by issues of data quality. We also offer a fourth explanation: that housing prices are driven by factors unrelated to local economic conditions. For example, an asset bubble in house prices would result in previous house price growth being the determining factor of current house price growth. Evidence for such exuberance is demonstrated in Greenaway-McGrevy and Phillips (2016) over the 2003 to 2016 period.[7]

Our work builds on Choy et al. (2002) and Grimes et al. (2009) in that we include rents. Rental price responses highlight that we must be careful to not conflate a lack of housing price inflation as a result of increased demand with a lack of increase to the current value of accommodation services. We find that rental prices do respond to labor market shocks and increase by substantially more than house prices. A simple explanation for this is that the rental channel represents the primary mode of accommodation for incoming workers. Intuitively this makes sense: prior to purchasing a house in a new region, workers to a region may choose to rent prior to purchase in order to identify the neighborhoods with the exact amenities they require. Furthermore, if the workers are transient by nature, and likely to repeat migrate, the rental market lacks the same level of 'lock-in' that home ownership does.

[7] Empirical tests for asset bubbles are based on testing whether suitably normalized asset prices exhibit periods of explosive I(2) behaviour. I(0) variables such as our shift-share labor demand and supply shocks have difficulty explaining the variation in house price growth rates that trend upward over time.

Our work also shows that there is a substantive migration response to regional shocks when compared to other countries, even after accounting for differences in housing supply elasticities. The substantial migration response is largely consistent with the narrative of Fredriksson (1999), who suggests that where regional populations are relatively small, the primary adjustment mechanism appears to be through the labour mobility channel due to a limited scope for industry switching following and employment demand shock.

7 Conclusion

This paper proposes a new satellite-based measure of housing supply restrictiveness and employs the measure in a model of regional adjustment in order to assess the impacts of regional variation is housing supply elasticities on labour and housing market outcomes in New Zealand. The new measure can be constructed based on publicly available satellite imagery data and complements existing measures of housing supply restrictions by providing an estimate of buildout. Applying the methods to labour market areas in New Zealand, we find that regions with more restrictive housing supply experience lower levels of employment and population growth, lower rates of housing construction, and a greater appreciation of rents after a positive economic shock.

Several directions of this research appear promising. First, the new satellite based measure can be computed at an annual frequency, raising the potential for examining both cross section and time series variation in housing restrictiveness. Second, the method can be applied in other models, such as spatial equilibrium treatments of agglomeration benefits and congestion costs of cities. Third, the method can be applied to other countries. We leave these areas for future research.

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8 Appendix

8.1 Conceptual framework

We adopt the conceptual model employed by Saks (2008) but make a minor adjustment to incorporate the broad employment rate. The economy is made up of a number of urban centres, indexed by i. (Inverse) labour demand in each of these areas and time t can be represented as:

$$w_{i,t} = -\delta(n_{i,t} - u_{i,t}) + z_{i,t} \tag{5}$$

where $w_{i,t}$ is the wage, $n_{i,t}$ is log of the labour force, $u_{i,t}$ is the unemployment rate, and $z_{i,t}$ is a constant for the (inverse) labour demand curve. Shifts in the labour demand curve are reflected by movements in $z_{i,t}$:

$$z_{i,t} - z_{i,t-1} = x_i^d + \epsilon_{i,t}^d \tag{6}$$

where x_i^d is a constant that captures any local characteristics that cause the labour demand to differ between regions, and $\epsilon_{i,t}^d$ represents a labour demand shock.

Over time the labour force responds to relative differences in real wages and city specific amenity benefits (x_i^s). Real wages can be considered as the difference between wages (w) and housing service prices (p). Therefore, migration can be expressed as:

$$n_{i,t} - n_{i,t-1} = \beta w_{i,t-1} - \phi p_{i,t-1} - \gamma u_{i,t} + x_i^s + \epsilon_{i,t}^s \tag{7}$$

Following the simplification of Saks (2008), in the case that the labour force is equal to the entire population and all workers consume a single unit of housing, equilibrium demand for housing reduces to be the size of the labour force. Demand for housing, assuming the housing stock is equal to the labour force, can thus be represented as:

$$p_{i,t} = \theta_i n_{i,t} + x_i^p \tag{8}$$

$$\theta_i = \theta_0 + \pi r_i + u_i \tag{9}$$

where x_i^p represents city specific housing market factors. Here θ_i represents the inverse of the elasticity of supply and is considered a function of the level of housing supply restrictiveness, r_i. A high value of θ_i implies that the housing supply is more inelastic. That is, a given an increase in the housing stock, a larger value of θ_i leads to a larger increase in housing prices. Through the parameter π in 9 differences in the level of housing supply responsiveness generate variation in the elasticity of housing supply. Thus, a positive value of π indicates that regions with restrictive housing supply environments have more inelastic housing supply.

8.2 House and Rental Price Indexes

Price growth is estimated via a hedonic imputation approach. The general specification for this is given in 10:

$$p_{i(t),t} = x'_{i(t),t}\beta_{1,t} + d'_{i(t),t}\beta_{2,t} + u_{i(t),t} \tag{10}$$

where $p_{i(t),t}$ denotes the log price of transaction $i(t)$ at time t, α_t is a constant term, $x_{i(t),t}$ is a vector of observable characteristics, $d_{i(t),t}$ is a vector of locational dummy variables, and $u_{i(t),t}$ is a standard error term. $i(t)$ indexes the houses i sold in time period t.

For the house price index our hedonic specification includes the attributes: land area, floor size, site intensity, number of bedrooms and bathrooms, building condition and age, and any appreciable views. Locational heterogeneity is also controlled for through the usage of dummy variables based on the statistical area unit (SAU) of the property. For rental prices, the available attributes are property type, number of bedrooms, and location (statistical area unit).

The hedonic imputation index then be obtained by estimating the following regression by OLS:

$$\hat{p}_{i(t),t} - \hat{p}_{i(t),t-1} = \gamma_t - \gamma_{t-1} + v_{i(t),t} \tag{11}$$

where $\hat{p}_{i,t}$ are the fitted (log) prices (rental or house) from the estimated hedonic regression. The price index is then given by $\left\{e^{\hat{\gamma}_t}\right\}_{t=1}^{T}$.

8.3 Additional Tables

Table 5: Panel Unit Root Tests

Pesaran (2007) panel unit root test (CIPS)		
Variable	Constant only	Constant & trend
Population (p)	-1.98	-2.36
Population growth (Δp)	-2.78***	-2.85**
Employment (e)	-1.84	-1.87
Employment growth (Δe)	-2.67***	-2.95***
Labour force (l)	-1.82	-1.99
Labour force growth (Δl)	-2.66***	-2.86***
Wages (w)	-2.01	-2.21
Wage growth (Δw)	-2.71***	-2.69**
House prices (hp)	-1.69	-2.11
House price growth (Δhp)	-2.42***	-2.62**
Rental prices (rp)	-1.77	-2.08
Rental price growth (Δrp)	-2.61***	-3.19***
Dwelling consents (hs)	-1.88*	-2.15

*,**,*** Denotes statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6: Impulse responses: Demand shock

Demand shock

Year	Part. rate	Empl. rate	Employment	Population	Labour force	Wages	HPI	RPI	Consents
All urban areas									
1	0.26	0.03	1.00	0.72	1.03	-0.04	0.03	0.24	0.60
	(0.22,0.30)	(0.01,0.04)	(1.00,1.00)	(0.68,0.76)	(1.00,1.06)	(-0.06,-0.02)	(-0.03,0.09)	(0.15,0.34)	(0.51,0.69)
3	0.04	0.01	0.56	0.52	0.56	-0.03	0.05	0.22	0.26
	(0.03,0.05)	(0.00,0.02)	(0.48,0.65)	(0.44,0.60)	(0.48,0.64)	(-0.04,-0.02)	(-0.01,-0.11)	(0.12,32)	(0.22,0.31)
5	0.01	0.00	0.51	0.51	0.51	-0.03	0.05	0.21	0.11
	(0.00,0.02)	(0.00,0.01)	(0.43,0.60)	(0.42,0.61)	(0.43,0.60)	(-0.04,-0.02)	(-0.01,-0.11)	(0.11,0.31)	(0.09,0.13)
10	0.00	0.00	0.51	0.51	0.51	-0.03	0.05	0.20	0.02
	(0.00,0.00)	(0.00,0.00)	(0.43,0.60)	(0.43,0.60)	(0.43,0.60)	(-0.04,-0.02)	(0.00,-0.11)	(0.11,0.31)	(0.01,0.03)
High restrictiveness urban areas									
Year	Part. rate	Empl. rate	Employment	Population	Labour force	Wages	HPI	RPI	Consents
1	0.20	0.06	1.00	0.72	0.94	-0.02	0.00	0.19	0.22
	(0.17,0.23)	(0.04,0.08)	(1.00,1.00)	(0.68,0.76)	(0.90,0.98)	(-0.03,-0.01)	(-0.03,0.03)	(0.14,0.24)	(0.11,0.33)
3	0.05	0.01	0.39	0.33	0.38	0.01	0.00	0.29	0.31
	(0.02,0.08)	(0.00,0.00)	(0.24,0.55)	(0.18,0.49)	(0.23,0.56)	(0.00,0.02)	(-0.03,0.03)	(0.24,0.34)	(0.16,0.45)
5	0.02	0.00	0.29	0.27	0.29	0.02	0.00	0.31	0.19
	(0.00,0.03)	(0.00,0.00)	(0.10,0.48)	(0.08,0.46)	(0.10,0.48)	(0.01,0.03)	(-0.03,0.03)	(0.26,0.37)	(0.04,0.33)
10	0.00	0.00	0.27	0.27	0.27	0.03	0.00	0.32	0.05
	(0.00,0.01)	(0.00,0.00)	(0.08,0.46)	(0.08,0.46)	(0.08,0.46)	(0.01,0.05)	(-0.03,0.03)	(0.26,0.37)	(-0.02,0.13)
Low restrictiveness urban areas									
Year	Part. rate	Empl. rate	Employment	Population	Labour force	Wages	HPI	RPI	Consents
1	0.16	0.15	1.00	0.67	0.84	0.06	-0.10	0.10	0.85
	(0.12,0.20)	(0.13,0.17)	(1.00,1.00)	(0.62,0.72)	(0.80,0.88)	(0.03,0.09)	(-0.14,-0.06)	(0.06,0.14)	(0.61,1.08)
3	-0.02	0.01	0.55	0.56	0.55	0.02	-0.11	0.06	0.12
	(-0.05,0.01)	(0.00,0.00)	(0.40,0.60)	(0.42,0.71)	(0.44,0.66)	(0.00,0.04)	(-0.15,-0.07)	(0.02,0.10)	(-0.05,0.29)
5	0.00	0.00	0.56	0.56	0.56	0.02	-0.11	0.05	0.07
	(0.00,0.00)	(0.00,0.00)	(0.42,0.71)	(0.42,0.71)	(0.42,0.71)	(0.00,0.04)	(-0.15,-0.07)	(0.01,0.09)	(0.00,0.14)
10	0.00	0.00	0.56	0.56	0.56	0.02	-0.11	0.05	0.01
	(0.00,0.00)	(0.00,0.00)	(0.42,0.71)	(0.42,0.71)	(0.42,0.71)	(0.00,0.04)	(-0.15,-0.07)	(0.00,0.08)	(0.00,0.02)

[para,flushleft] Impulse response estimates for each model at selected years after the initial shock in year 1.
90% confidence intervals are calculated via Efron (1981) bootstrapping and are given in parenthesis.

Table 7: Impulse responses: Supply shock

Supply shock

Year	Part. rate	Empl. rate	Employment	Population	Labour force	Wages	HPI	RPI	Consents
All urban areas									
1	0.33	-0.08	1.00	0.76	1.06	-0.03	0.00	0.12	0.91
	(0.29,0.37)	(-0.10,-0.06)	(1.00,1.00)	(0.71,0.80)	(1.03,1.09)	(-0.04,-0.02)	(-0.05,0.05)	(0.08,0.016)	(0. 81,1.01)
3	0.04	0.01	0.62	0.57	0.61	-0.02	0.02	0.09	0.44
	(0.03,0.05)	(0.00,0.02)	(0.52,0.72)	(0.46,0.67)	(0.51,0.71)	(-0.03,-0.01)	(-0.04,0.08)	(0.05,0.13)	(0.36,0.52)
5	0.01	0.00	0.57	0.57	0.57	-0.02	0.02	0.07	0.19
	(0.00,0.02)	(0.00,0.00)	(0.47,0.67)	(0.46,0.66)	(0.46,0.67)	(-0.03,-0.01)	(-0.03,0.09)	(0.03,0.11)	(0.16,0.21)
10	0.00	0.00	0.57	0.57	0.57	-0.02	0.03	0.05	0.03
	(0.00,0.00)	(0.00,0.00)	(0.47,0.67)	(0.47,0.67)	(0.47,0.67)	(-0.03,-0.01)	(-0.03,0.06)	(0.01,0.09)	(0.02,0.04)
High restrictiveness urban areas									
Year	Part. rate	Empl. rate	Employment	Population	Labour force	Wages	HPI	RPI	Consents
1	0.26	-0.02	1.00	0.76	1.02	0.00	-0.05	0.14	0.51
	(0.21,0.31)	(-0.04,0.00)	(1.00,1.00)	(0.72,0.80)	(0.99,1.03)	(-0.02,0.02)	(-0.08,-0.02)	(0.09,0.18)	(0.39,0.63)
3	0.12	0.02	0.79	0.65	0.77	0.02	-0.01	0.14	0.36
	(0.07,0.17)	(0.01,0.03)	(0.62,0.95)	(0.49,0.81)	(0.60,0.93)	(-0.00,0.04)	(-0.04,0.02)	(0.08,0.19)	(0.22,0.48)
5	0.07	0.01	0.62	0.53	0.61	0.03	0.01	0.15	0.25
	(0.03,0.10)	(0.00,0.02)	(0.42,0.82)	(0.35,0.72)	(0.41,0.80)	(0.01,0.05)	(-0.03,0.05)	(0.07,0.23)	(0.15,0.35)
10	0.03	0.00	0.45	0.45	0.45	0.05	0.02	0.16	0.09
	(0.00,0.06)	(0.00,0.01)	(0.24,0.66)	(0.24,0.66)	(0.24,0.66)	(0.02,0.07)	(-0.02,0.06)	(0.8,0.24)	(0.05,0.13)
Low restrictiveness urban areas									
Year	Part. rate	Empl. rate	Employment	Population	Labour force	Wages	HPI	RPI	Consents
1	0.23	-0.07	1.00	0.88	1.06	-0.09	0.03	0.03	0.82
	(0.19,0.27)	(-0.08,-0.04)	(1.00,1.00)	(0.82,0.94)	(1.03,1.09)	(-0.11,-0.07)	(0.00,0.06)	(0.00,0.06)	(0.65,0.99)
3	0.02	0.01	0.87	0.86	0.85	-0.06	-0.03	-0.04	0.38
	(-0.01,0.04)	(0.00,0.02)	(0.74,1.00)	(0.73,0.99)	(0.73,0.99)	(-0.08,-0.04)	(-0.07,-0.01)	(-0.07,0.01)	(0.16,0.60)
5	0.00	0.01	0.86	0.86	0.86	-0.07	-0.06	-0.07	0.17
	(-0.01,0.01)	(0.00,0.01)	(0.73,0.99)	(0.73,0.99)	(0.73,0.99)	(-0.09,-0.05)	(-0.10,-0.01)	(-0.10,-0.04)	(0.07,0.28)
10	0.00	0.00	0.86	0.86	0.86	-0.06	-0.07	-0.07	0.03
	(0.00,0.00)	(0.00,0.00)	(0.73,0.99)	(0.73,0.99)	(0.73,0.99)	(-0.08,-0.04)	(-0.11,-0.2)	(-0.10,0.04)	(0.00,0.06)

[para,flushleft] Impulse response estimates for each model at selected years after the initial shock in year 1.
90% confidence intervals are calculated via Efron (1981) bootstrapping and are given in parenthesis.

Table 7: Labour Market Areas

	LMA	TLA	population
1	Whangarei	Whangarei District	68,100
		Kaipara District	21,300
2	Auckland	Auckland City	1,098,100
3	Hamilton	Waikato District	57,800
		Hamilton City	108,000
		South Waikato District	6,700
4	Taupo	Taupo District	31,600
5	Tauranga	Western Bay of Plenty District	30,800
		Tauranga City	84,700
6	Rotorua	South Waikato District	17,800
		Rotorua District	45,000
		Whakatane District	24,100
		Kawerau District	2,200
7	Gisborne	Gisborne District	37,900
		Wairoa District	3,600
8	Napier & Hastings	Hastings District	52,400
		Napier City	39,800
9	New Plymouth	New Plymouth District	61,000
		Stratford District	6,500
		South Taranaki District	16,300
10	Whanganui	Whanganui District	34,700
11	Palmerston North	Manawatu District	20,900
		Palmerston North City	52,500
		Horowhenua District	26,700
12	Paraparaumu	Kapiti Coast District	33,900
13	Wellington	Porirua City	50,400
		Wellington City	129,300
14	Lower Hutt	Upper Hutt City	20,200
		Lower Hutt City	105,500
15	Masterton	Masterton District	20,200
		Carterton District	7,900
		South Wairarapa District	6,700
16	Nelson	Nelson City	45,400
		Tasman District	27,100
17	Blenheim	Marlborough District	36,400
		Kaikoura District	3,600
18	Christchurch	Waimakariri District	13,100
		Christchurch City	320,600
		Selwyn District	28,500
19	Timaru	Ashburton District	25,900
		Timaru District	25,700
		Mackenzie District	3,800
		Waimate District	6,900
		Waitaki District	10,100
20	Queenstown	Central Otago District	10,200
		Queenstown-Lakes District	18,000
21	Dunedin	Dunedin City	122,400
		Clutha District	15,600
22	Invercargill	Gore District	49,500
		Southland District	18,700
		Invercargill City	49,500